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Author academic influence and manuscript acceptance: Evidence from peer review in cell press journals

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ABSTRACT

Background: Prior studies on peer review have largely focused on manuscript characteristics as the primary determinants of acceptance decisions. Although author academic influence is widely recognized in practice as a contributing factor, it has received limited attention in the academic literature, mainly due to data constraints.

Methods: Using a unique dataset of manuscript submissions to Cell Press journals, we examine how author academic influence relates to peer review outcomes.

Results: We find that author academic influence is positively associated with manuscript acceptance, with this effect particularly pronounced for junior researchers.

Conclusions: Our analysis indicates that author academic influence functions as a signal of a manuscript's impact, thereby enhancing its likelihood of acceptance.

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Peer review; academic influence; signaling effect; cell press journals

1. Introduction

Peer review, which serves as the cornerstone of scientific communication, plays an important role in the dissemination and validation of research (Chescheir 2018, 2019, 2025). The decisions made during the peer review process, as well as the criteria for selecting papers, have been a central focus of scholarly inquiry (Bornmann 2011; Merton 1968). From the perspective of scientific norms, manuscript acceptance is traditionally viewed through the lens of Merton's concept of Universalism, where in the evaluation of claims in scientific discourse is based primarily on their inherent scientific merit, rather than on the personal or social characteristics of the authors presenting them (Merton 1968, 1973). However, the manuscript acceptance process extends beyond the characteristics of the manuscript itself (Garcia et al. 2024; Garcia, Rodriguez-Sanchez, and Fdez-Valdivia 2019, 2022). In practical terms, many researchers have observed that author-related factors also play

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a significant role in shaping peer review outcomes. Specifically, author academic influence appears to be a crucial determinant in manuscript acceptance, often favoring more established researchers. This phenomenon highlights the impact of individual researcher characteristics, where well-known authors may disproportionately increase their chances of acceptance, exemplifying the Matthew effect in academic publishing.

The core problem addressed in this study is the potential bias in the manuscript acceptance process, particularly how author academic influence may shape peer review outcomes, potentially privileging established researchers over emerging ones. This issue is especially important because peer review decisions impact the academic careers of researchers, potentially shaping who gets recognition, funding, and career advancement. Understanding this dynamic is crucial for ensuring fairness in the scientific communication and production.

Although academia has recognized this issue, the availability of relevant peer review data, such as authors' submission histories and review outcomes, has been limited, hindering a more comprehensive investigation. On the one hand, due to the sensitivity of peer review data, even agreements with publishers to access this information often result in anonymized datasets, where author identities are concealed (Teplitskiy et al. 2018). On the other hand, even within the open peer review movement, the available information is typically restricted to peer review reports of already published papers, excluding data on manuscripts that were rejected (Zhang, Wang, and Wang 2024). While previous studies have attempted to address this issue through experimental approaches (Huber et al. 2022; Okike et al. 2016; Peters and Ceci 1982), their conclusions remain limited by small sample sizes or a lack of generalizability. This study differs by leveraging a large, real-world dataset that includes both accepted and rejected manuscripts, offering a more comprehensive view of the role of academic influence in manuscript acceptance.

Second, the specific nature of the impact of academic influence on manuscript acceptance remains unclear. The potential effect of academic influence on manuscript acceptance is likely to vary across different author groups. For established researchers, who typically possess a relatively high level of academic influence, the marginal effect of this influence may be relatively small, as their established reputation already ensures a significant degree of acceptance. In contrast, junior scientists – whose academic influence is generally lower – may experience a more pronounced effect, where their academic standing can substantially increase the likelihood of their manuscript's acceptance.

Finally, while there has been growing interest in the role of academic influence in the peer review process, there remains a notable gap in the literature regarding the mechanisms through which academic influence relates to manuscript acceptance decisions.

This study uses last author citation as a proxy for academic influence and analyzes more than 4,000 manuscripts from Cell Press journals. Our results reveal a relationship between author academic influence and manuscript acceptance, with a stronger relationship among junior authors. Additionally, we examine the signaling mechanism underlying this relationship, proposing that author academic influence enhances manuscript acceptance by signaling impact.

This study contributes to three strands of literature. First, it extends research on peer review and the Matthew effect by introducing a unique dataset that includes both accepted and rejected submissions, allowing us to link author academic influence to peer review outcomes. Second, it uncovers heterogeneous effects across different author groups, showing that academic influence matters more for junior than senior authors, thereby enriching the literature on inequality in science. Third, it proposes and tests a signaling effect through which academic influence may shape peer review outcomes, helping to explain how editors and reviewers evaluate manuscripts under uncertainty.

The remainder of the paper is organized as follows. The "Theory and hypothesis" section presents the theory background and hypothesis development. "Data and methodology" section describes the data sources, the operationalization of key variables such as author academic influence and manuscript acceptance, and the empirical strategy. "Empirical results" section presents the main results, subgroup results and mechanism analysis results. "Discussion and conclusion" section concludes with a discussion of tentative explanations, implications, and limitations.

2. Theory and hypothesis

2.1. *Peer review and Matthew effect*

In general, scientists acknowledge and endorse the principles of Universalism (Merton 1968, 1973), asserting that peer review should be based on manuscript itself. However, adhering to this norm in practice poses challenges, as biases rooted in the academic influence of authors can influence peer review outcomes (Long and Fox 1995). The Matthew effect – a concept introduced by Merton (1968)—describes the cumulative advantage that well-established scientists receive, which further enhances their recognition and success. Consequently, a select few scientists with notable achievements often garner disproportionate recognition for their discoveries (Cole and Cole 1973). In the context of peer review, this phenomenon suggests that authors with higher academic influence are more likely to have their manuscripts accepted. This effect can manifest in the preferential treatment of manuscripts authored by well-known researchers, leading to an unequal distribution of opportunities and recognition in academia (Shopovski, Bolek, and Bolek 2020; Tomkins, Zhang, and Heavlin 2017).

Several experiments (Huber et al. 2022; Okike et al. 2016; Peters and Ceci 1982) support the view that peer review is not solely guided by the manuscript itself but also by the academic influence of author. Such biases in the peer review process have led to calls for double-blind peer review as a means of reducing author identity biases and enhancing fairness in scientific evaluation (Darling 2015; Tomkins, Zhang, and Heavlin 2017). However, the effectiveness of double-blind peer review is questionable. Authors often struggle to fully erase their identities in specialized fields, as reviewers can frequently deduce author identities based on prior work (Chung et al. 2015; DeCoursey 2015; Martin 2017). Moreover, in practice, fewer than 20% of submissions opt for double-blind review in journals like *Nature Geoscience* and *Nature Climate Change*, as reported in Nature (2015).

Given the growing recognition of the potential biases in traditional peer review processes, some have argued that open peer review, which emphasizes transparency, may better address these biases (Bravo et al. 2019). Simultaneously, the expansion of open science, coupled with the rise of preprint platforms like arXiv, bioRxiv, Social Science Research Network (SSRN), has accelerated the disclose and dissemination of scientific findings. However, this trend has also made the preservation of double-blind peer review more challenging within the current scientific communication system.

2.2. *Differential effects across authors with varying levels of academic influence*

Under the Matthew Effect, the influence of peer review varies for scholars with different academic influence. Empirical studies in areas such as author credit (Seeman and House 2010, 2015) and funding reviews (Daniels 2015) also suggest that junior researchers face greater disadvantages. Esteemed scholars often maintain favorable relationships with journals and potential reviewers (Murray et al. 2018), making it difficult for editors and reviewers to discriminate against them. Consequently, the impact of academic influence is less observable among highly reputable scholars, as they are widely recognized figures within the academic community. In contrast, for lesser-known scholars, particularly junior researchers, academic influence can play a more significant role in peer review outcomes. This disparity is one reason some studies argue that double-blind peer review may benefit junior researchers more (Darling 2015; Tomkins, Zhang, and Heavlin 2017).

2.3. *Signaling effect*

Long and Fox (1995) contend that Universalism weakens, and author identity becomes more influential when there is scant information to reflect manuscript itself, evaluation criteria is unclear, and the review process is closed. Actually, evaluating the potential quality of manuscripts proves challenging for journals. Even editors from renowned journals, such as the *British Medical Journal* (BMJ), struggle to accurately estimate the citation potential of manuscripts (Schroter et al. 2022). In a similar situation, to mitigate this uncertainty, sellers, such as authors submitting manuscripts to journals, can send signals indicating high quality to buyers, such as journals, to showcase their potential (Connelly et al. 2011; Spence 1973).

This phenomenon is not uncommon in academia. For instance, in employment and tenure track evaluations, external reputation may signify a form of recognition, even if that recognition is not directly related to higher scientific competence (Baldi 1995; Keith and Babchuk 1998; Schröder, Lutter, and Habicht 2021). Similarly, author academic influence can be meaningful in peer review. Adair (1982), an editor of a physics journal, argue that although reviews may not assign significant weight to an author's academic influence, work produced by scientists who have gained prestige through a history of important and successful research is more credible than work produced by average scientists. In current research culture marked by increasing competition and rising misconduct, a researcher's academic influence serves as a form of quality assurance for reviewers (DeCoursey 2015). Therefore, an author's academic influence may send a signal and provide an endorsement of studies, potentially benefiting the acceptance of manuscripts.

2.4. *Hypotheses*

Although scholarly attention to peer review has increased in recent years, there is still a lack of empirical research that systematically explores how academic influence operates in shaping review outcomes. In particular, little is known about whether the effect of author influence varies across career stages, or whether such influence functions as a signal of potential impact. To address these gaps, the following hypotheses were developed based on prior theoretical and empirical work before conducting our main empirical analysis.

H1: There is a positive relationship between author academic influence and the likelihood of manuscript acceptance.

H2: The relationship between author academic influence and the likelihood of manuscript acceptance will be more strongly positive among junior authors.

H3: Among junior authors, author academic influence signals the impact of the manuscript, which in turn increases the likelihood of manuscript acceptance.

These hypotheses were grounded in the literature on the Matthew effect, signaling theory, and peer review dynamics. Our empirical work was designed to test these theory-driven expectations.

2.4.1. Data and methodology

3.1. *Data*

Our empirical analysis draws on unique original submission data from SSRN, with additional bibliometric information matched from Web of Science and Scopus for each published paper. Cell Press provides a feature called "Sneak Peek" within SSRN (https://www.cell.com/sneakpeek) as part of their efforts to enhance the publishing process and expedite the dissemination of scho larly research. Compared to other preprint platforms, SSRN not only pro vides access to manuscript content and author information but also includes information on the publication status of each manuscript.[1] Notably, the visibility of author information on SSRN means that author identity is publicly accessible at the time of manuscript dissemination.

A total of 5,248 manuscripts were collected from SSRN. For manuscripts with a publication status of "Published," the journal name was directly obtained. For manuscripts with a publication status of "Review Complete" or "Under Review," we employed the identification strategy proposed by Casnici et al. (2017), Scherer et al. (2018) and Schroter et al. (2022). This involved entering key parts of the submitted manuscript title, author names, or elements of the abstract into Google's search engine to try to match submissions with subsequent publications. This search was conducted between November 2021 and November 2022. If the first searcher could not find a publication, a second researcher tried, and final decisions were based on discussion and agreement. In addition, following the approach of Scherer et al. (2018), we chose not to update the search once more than 85% of full manuscripts were obtained, as additional searches were deemed unlikely to significantly alter our overall conclusions. This resulted in 4,552 publications, representing 86.73% of the total manuscripts.

Information on the last author was retrieved from Scopus to obtain total citation counts and total publication counts (Salter, Salandra, and

Walker 2017; Teplitskiy et al. 2018; Walker et al. 2019). The manuscripts were subsequently matched in Scopus to collect bibliometric data on 8 February 2025, including citation counts. Additionally, we retrieved the impact factors of the journals in which the papers were published from Web of Science. Finally, after excluding cases with missing data, a total of 4,029 items were included in our empirical analysis. Gender information for authors was inferred using a name-based gender inference system developed by Gu et al. (2016), which incorporates both the authors' names and affiliated institutions. Of the total sample, gender for 3,349 authors was determined automatically using this system. For an additional 680 authors whose gender could not be confidently inferred by the algorithm, we conducted manual verification based on publicly available information (e.g., personal websites or institutional profiles). It is important to note that, given the availability and comparability of the data, in the manuscripts analyzed, "accepted manuscripts" refer to those that were accepted for publication after submission, while "rejected manuscripts" refer to those that were not accepted but were transferred to other journals for publication.[2]

3.2. *Variables*

3.2.1. *Dependent variable*

Acceptance is a binary outcome. This binary variable is coded as "1" if the manuscript was accepted and "0" otherwise.

3.2.2. *Independent variables*

Author academic influence (*Academic influence*) Previous empirical studies support the notion that bibliometric indicators, particularly an author's citation count, are strong indicators of their academic influence (Guba and Tsivinskaya 2023; Salter, Salandra, and Walker 2017; So 1998; Walker et al. 2019). In the context of biomedical and life sciences research, the last author often occupies the most senior or supervisory role, typically reflecting the principal investigator who conceptualizes and oversees the study. This convention is especially entrenched in these fields, where authorship order carries symbolic meaning and the last position is reserved for those with the highest academic influence (Abdill, Adamowicz, and Blekhman 2020; Sekara et al. 2018). Therefore, citation counts of last authors provide not only a measure of scholarly impact, but also a meaningful proxy for the perceived status and identity of the author within the scientific community.

Although this practice may vary across different scientific disciplines, it remains a well-established proxy in the biomedical domain.[3] Compared to the h-index, citation counts are more sensitive to academic influence at specific points in time – such as at manuscript submission – making them better suited for capturing temporal variations in author influence. Therefore, in our analysis, we use the number of citations of the last author prior to manuscript submission as a measure of the author's academic influence (*Academic Influence*) (Salter, Salandra, and Walker 2017; Walker et al. 2019; Zhang et al. 2022, 2023).

Some prior studies normalize citation counts by career age or total number of publications to adjust for differences in academic stage. However, we intentionally use raw citation counts to capture the full visibility and recognition of an author at the time of submission, since this accumulated reputation is likely to influence peer review decisions. Normalizing these values would risk masking the structural advantage held by senior scholars, which is precisely the mechanism theorized in the Matthew effect and under investigation in this study.

3.2.3. *Control variables*

Paper impact (*Short-term impact*, and *Long-term impact*) Previous studies have shown high correlations between citation counts and evaluation outcomes (Ellis and Durden 1991; Franceschet and Costantini 2011; So 1998). In paper evaluation, various empirical studies have used bibliometric indicators as an approximate measure of the inherent quality of papers, given the positive correlation between these indicators and peer review outcomes (Franceschet and Costantini 2011; Wainer and Vieira 2013). Some studies argue that citation counts serve as a proxy for assessing paper quality in peer review (Card and DellaVigna 2020; Paine and Fox 2018), while others suggest that citations are more accurately seen as an indicator of visibility or impact rather than inherent quality itself (Aksnes, Langfeldt, and Wouters 2019). Nevertheless, given that citation counts are among the most quantifiable and unbiased objective metrics available for measuring a paper's impact, we utilize citation counts from Scopus as a measure of paper impact.

Thus, we include two citation variables: the number of citations received in the publication year and the following two years (*Short-term impact*) and the total citations accumulated from publication until 7 February 2025 (*Long-term impact*). The short-term citation measure captures the paper's early visibility after publication, while the long-term citation measure reflects its sustained recognition. By controlling for these variables, we aim to more accurately reveal the effect of author academic influence on peer review outcomes.

Target JIF We use the impact factor of the target journal in the year of the manuscript's submission to construct the Target JIF variable. Using the Target JIF offers two distinct advantages. First, we treat the impact factor of the target journal (i.e., the journal to which the manuscript was submitted) as a proxy for the author's own perception of the manuscript's quality. In other words, we interpret the decision to submit to a higher-impact journal as a revealed preference for higher expected quality or visibility. Given the substantial submission costs and long peer review timelines, authors are more likely to send manuscripts they believe to be of higher impact to journals with higher impact. This approach is consistent with prior research (Calcagno et al. 2012; Pepermans and Rousseau 2016), which suggests that authors' choice of target journal serves as a strategic signal that reflects their subjective assessment of the manuscript's quality. Second, it is widely acknowledged that higher-impact journals impose greater publication challenges. They receive more submissions and apply stricter selection criteria (Gaston et al. 2020; Sugimoto et al. 2013). Including Target JIF allows us to control for both author-side submission behavior and journal-side publication difficulty, thereby isolating the effects of author academic influence more precisely. While we recognize the limitations of using JIF as a quality proxy, we emphasize that we do not treat it as a direct measure of paper quality, but rather as an indicator of the broader publication environment.

We employed citation count to measure author academic influence and paper impact; however, given its wide acceptance as a measure of journal influence, we obtained journal impact factors from the Journal Citation Reports. Although these impact factors are computed using data from Web of Science rather than Scopus, our focus is on their scientific significance rather than solely on their citation properties.

Male Previous studies suggest that female authors might face biases in scientific system (Murray et al. 2018; Squazzoni et al. 2021). Thus, we control for the gender of the last author using a dummy variable (coded as "1" for male and "0" for female).

US Author's national affiliation may also be related to academic influence and peer review outcomes, potentially reflecting home bias, where manuscripts from authors affiliated with institutions in certain countries or regions may receive preferential treatment (Murray et al. 2018; Rubin, Rubin, and Segal 2023). For instance, US reviewers may give more favorable recommendations to manuscripts from US authors (Link 1998). Since the journals in our dataset are located in the US, editors may be more inclined to invite US reviewers (Espin et al. 2017). Therefore, we introduce a variable to control for US authorship, where "*US*" is a dummy variable coded as 1 if the last author works in the US and 0 otherwise.

We also control for variables at the paper level that may relate both to author academic influence and the likelihood of manuscript acceptance.

Number of authors From the perspective of scientific production, authors with higher academic influence are likely to collaborate with larger teams. The increase in the number of authors can facilitate the pooling of diverse expertise, which may increase the likelihood of manuscript acceptance due to the enhanced comprehensiveness of the research.

Number of references, and Number of pages While these metrics are not direct measures of research quality or author expertise, they may reflect differences in article complexity, scope, or theoretical engagement. Including them helps mitigate potential confounding in the relationship between author academic influence and peer review outcomes.

Time fixed effect (YM) To address the potential issue of citation window bias, we control for Year-Month fixed effects based on the time when the manuscript was first posted on SSRN, rather than its publication date. This ensures that we account for the specific temporal context in which the manuscript's visibility and citation patterns may evolve.

Table 1 provides definitions for the variables, while Table 2 present descriptive statistics and a pairwise correlation matrix of the variables.

Descriptive statistics and spearman correlation tests are reported in Table 2. The proportion of accepted manuscripts in the dataset is 64%. These papers were published across 400 journals between 2017 and 2023. The mean short-term citation count for these papers is 27.11 (ranging from 0 to 1,409), while the mean long-term citation count is 48.09 (ranging from 0 to 1,767). Male researchers serve as the last authors in 77% of cases, with 41% of these last authors affiliated with institutions in the United States. On average, authors have accumulated total of 7,135 citations (ranging from 0 to 237,379). To reduce data variability, following the recommendations of Changyong et al. (2014), we applied a log transformation to independent variables, using the transformed values instead of the original ones. Specifically, we used the function ln(independent variable + 1) for this purpose. Each paper in the dataset has an average of 11.55 authors, cites 64.49 references, and spans 19.78 pages. The average impact factor of the target

Table 1. Variable descriptions.

Construct	Variable	Type	Description
Dependent	*Acceptance*	dummy	1 if the decision was accepted; 0 was not accepted.
Independent	*Academic influence*	count	The total number of citations received by the last author's publications prior to the manuscript submission.
Control	*Short-term impact*	count	Number of citations an article receives in Scopus during the publication year and the following two years.
	Long-term impact	count	The cumulative number of citations an article has received in Scopus since its publication.
	Target JIF	count	Impact factor of the journal to which the manuscript was initially submitted, measured in the year the manuscript was posted.
	Male	dummy	1 if the last author was male; 0 was female.
	US	dummy	1 if the last author was a scientist based in the United States; 0 otherwise.
	No. of authors	count	Number of coauthors.
	No. of references	count	Number of references.
	No. of pages	count	Number of pages.
	YM	dummy	Post publication year and month on SSRN.

Table 2. Correlation matrix and descriptive statistics (including ranges) of applied variables (N = 4,029).

		1	2	3	4	5	6	7	8	9	10
1	*Acceptance*	1.00									
2	*Short-term impact*	0.06	1.00								
3	*Long-term impact*	0.07	0.91	1.00							
4	*Academic influence*	−0.01	0.08	0.10	1.00						
5	*Target JIF*	−0.20	0.36	0.34	0.14	1.00					
6	*Male*	−0.01	0.01	0.02	0.10	0.04	1.00				
7	*US*	0.00	0.05	0.08	0.12	0.13	0.00	1.00			
8	*No. of authors*	−0.00	0.35	0.36	0.06	0.26	−0.02	0.00	1.00		
9	*No. of references*	0.03	0.04	0.03	−0.01	0.12	−0.05	0.10	0.11	1.00	
10	*No. of pages*	0.17	0.07	0.06	−0.00	0.08	−0.05	0.03	0.13	0.30	1.00
	Mean	0.64	27.11	48.09	7135.52	15.14	0.77	0.41	11.55	64.49	19.78
	S.D.	0.48	53.58	85.14	13609.1	12.16	0.42	0.49	9.78	22.99	10.08
	Min	0	0	0	0	4.45	0	0	1	3	2
	Max	1	1409	1767	237379	66.85	1	1	204	221	260

journals is 15.14. Variance inflation factor (VIF) scores were all well below the conventional threshold of 10, with the maximum value at 1.45, indicating that multicollinearity is not a concern.

3.3. *Methods*

The following model was employed:

$$Acceptance_i = \alpha_0 Academic\,influence_i + \alpha_1 Controls_i + \varepsilon_i (i = 1, \ldots, n) \quad (1)$$

The dependent variable under consideration is denoted as $Acceptance_i$. $Academic\ influence_i$ refers to the academic influence of the author. The term $Controls_i$ encompasses additional control variables, and ε_i denotes the error term. Our focus lies in the estimation of coefficient α_0, elucidating the relationship between author academic influence, and peer review outcomes.

To account for potential heterogeneity among authors (Sakai 2019; Zhang et al. 2022), we categorize authors into three groups based on the tertiles of citation counts of the last author at the time of submission: *Junior*, *Intermediate*, and *Senior*. Specifically, junior authors are in the bottom third of the citation distribution, intermediate in the middle third, and senior in the top third.

To further investigate the signaling effect, we employ mediation analysis. As previously discussed, the uncertainty regarding the impact and reliability of papers presents challenges for journals and reviewers when making peer review decisions. However, this decision-making process is facilitated when endorsed by esteemed authors, suggesting that paper impact mediates the relationship between author academic influence and acceptance. Equation (2) specifies the regression of the independent variable *Academic influence*$_i$ on the dependent variable *Accept*$_i$. Subsequently, Equation (3) represents the regression of the independent variable *Academic influence*$_i$ on the mediator variable *Paper impact*$_i$. We include variables reflecting both short-term and long-term citation impact in the mediation analysis. Since the dependent variable *Acceptance* is binary, we estimate the model using logit regression.

$$Acceptance_i = \beta_0 Academic\,influence_i + \beta_1 Controls_i + e_1 \tag{2}$$

$$Paperimpact_i = \gamma_0 Academic\,influence_i + \gamma_1 Controls_i + e_2 \tag{3}$$

4. Empirical results

4.1. *Main results*

Table 3 reports the results from the logit regression models specified in Equation (1), examining the relationship between author academic influence and the likelihood of manuscript acceptance.

Columns (1) and (2) focus on author-level academic influence. Column (1) includes only the *Academic influence* variable and *Target JIF*, while Column (2) adds a full set of control variables. In both models, the coefficient on *Academic Influence* is positive and statistically significant at the 1% level, indicating that higher academic influence is associated with a greater probability of manuscript acceptance.

Columns (3) and (4) shift attention to the impact of paper, incorporating short-term and long-term citation measures, respectively. Both citation-based indicators are positively and significantly related to manuscript acceptance, with the coefficient on long-term impact (0. 662) being notably larger, suggesting a stronger association.

Columns (5) and (6) include both paper-level impact and author academic influence. In these fully specified models, *Academic influence* remains positively and significantly associated with acceptance, even after accounting for paper impact. Our findings support H1, demonstrating a statistical relationship between author academic influence and the likelihood of manuscript acceptance.

Furthermore, it is important to highlight differences in the coefficients of control variables relative to prior studies. In particular, the coefficient for *Target JIF* is consistently negative and statistically significant at least at the 0.01 level, which is in line with the expectation that journals with higher impact factors tend to have lower acceptance rates. Notably, we did not find support for claims that manuscripts with male last authors or those affiliated with institutions in the United States are more likely to be accepted (Murray et al. 2018).

Table 3. Main regression results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Academic influence		Paper impact		All variables	
	Single variable	All variables	Short-term	Long-term	Short-term	Long-term
Academic influence (ln)	0.067***	0.076***			0.057***	0.047**
	(0.019)	(0.020)			(0.021)	(0.021)
Short-term impact (ln)			0.531***		0.521***	
			(0.046)		(0.046)	
Long-term impact (ln)				0.662***		0.653***
				(0.046)		(0.046)
Target JIF	−0.034***	−0.047***	−0.065***	−0.070***	−0.066***	−0.071***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Male		−0.006	0.001	−0.005	−0.020	−0.023
		(0.084)	(0.085)	(0.086)	(0.085)	(0.087)
US		0.119	0.104	0.090	0.083	0.073
		(0.073)	(0.074)	(0.075)	(0.074)	(0.075)
No. of authors		0.004	−0.008**	−0.011***	−0.008**	−0.011***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
No. of references		−0.007***	−0.008***	−0.008***	−0.008***	−0.008***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
No. of Pages		0.094***	0.097***	0.097***	0.097***	0.097***
		(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Constant	0.596***	0.678	0.236	−0.012	−0.118	−0.309
	(0.154)	(0.421)	(0.402)	(0.407)	(0.425)	(0.430)
Observations	4029	4029	4029	4029	4029	4029
ll	−2547.06	−2363.32	−2299.85	−2253.75	−2296.28	−2251.31
aic	5100.12	4830.64	4703.71	4611.50	4698.55	4608.62
bic	5119.03	5158.30	5031.37	4939.17	5032.52	4942.59
YM	No	Yes	Yes	Yes	Yes	Yes

" >1) Standard errors in parentheses. 2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 3) A list of journals and additional regression results excluding *Matter*, *Chem*, and *One Earth* are provided in the supplementary materials.

4.2. *Different effect among various authors*

The role of author academic influence in manuscript acceptance emerges as a significant factor in our overall analysis. In Columns (1), (3), and (5), the Short-term impact variable is incorporated, whereas in Columns (2), (4), and (6), the Long-term impact variable is included.

Table 4 reveals noteworthy distinctions among these author groups. For *Junior*, the coefficients for *Academic influence* are positive and statistically significant at the 0.05 level in Column (1) and at the 0.1 level in Column (2). This indicates a significant correlation between author academic influence with peer review outcomes for junior researchers. For instance, in Column (1), a one-standard deviation increase in *Academic influence* corresponds to an 8.3% rise in manuscript acceptance (exp(0.080) − 1). However, the results in Columns (3)-(6) demonstrate that only the coefficients associated with paper impact remain positive and significant, while those of *Academic influence* are not statistically significant. These findings suggest that, for junior researchers, manuscripts authored by individuals with higher academic influence are more likely to be accepted. However, such an effect is

Table 4. Regression results for authors with various academic influence.

	(1) *Junior*	(2) *Junior*	(3) *Intermediate*	(4) *Intermediate*	(5) *Senior*	(6) *Senior*
Academic influence (ln)	0.080**	0.074*	0.059	0.043	−0.051	−0.051
	(0.038)	(0.038)	(0.191)	(0.192)	(0.092)	(0.092)
Short-term impact (ln)	0.497***		0.546***		0.590***	
	(0.079)		(0.083)		(0.085)	
Long-term impact (ln)		0.710***		0.719***		0.634***
		(0.080)		(0.086)		(0.081)
Constant	−0.044	−0.315	−0.349	−0.638	1.032	0.932
	(0.744)	(0.780)	(1.655)	(1.671)	(1.157)	(1.166)
Observations	1334	1334	1344	1344	1349	1349
loglikelihood	−769.88	−746.29	−749.37	−733.16	−727.85	−719.95
aic	1643.76	1596.57	1602.74	1570.31	1559.70	1543.89
bic	1913.95	1866.76	1873.31	1840.89	1830.47	1814.67
YM	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

" >1) Standard errors in parentheses. 2) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. 3) Estimates can be interpreted by taking the exponential of the coefficient and subtracting 1: exp(0.080)−1= 0.083.

less discernible among intermediate and senior researchers. These outcomes support H2. It is also worth noting that the inclusion of long-term impact, as opposed to short-term impact, reduces the statistical significance of *Academic influence*. This implies that the observed effect of author influence may partially overlap with the long-term scholarly impact of the paper.

These results may reflect the diminishing marginal returns of academic influence in the peer review process. For authors who are already well-known within their fields, additional increments in academic influence may not meaningfully alter editors' or reviewers' perceptions – both are considered reputable scholars. As such, the marginal benefit of having greater academic influence is relatively limited among these groups. In contrast, among junior researchers – who often lack established reputations – differences in academic influence may play a more prominent role in shaping how editors and reviewers perceive their scholarly potential or credibility. In such cases, academic influence may carry greater weight in the peer review process.

4.3. *Why does name matter?*

Having established a correlation between academic influence and peer review outcomes, we proceed to investigate three possible interpretations concerning the role of such prominence: the journal effect, gender and home effect, and the signaling effect. As delineated in the introduction, making distinctions among these pathways is instrumental in comprehending the ramifications of our findings with respect to elucidating the intricacies of the peer review process.

4.3.1. *Journal effect*

First, given the diverse gatekeeping instructions inherent in various journals (Seeber 2020), our initial consideration involves an examination of the relationship between author academic influence and the journal's impact factor among junior authors. In other words, do junior authors tend to submit manuscripts to journals with relatively low impact factors? To examine this aspect, we conducted a regression to test the relationship between author academic influence and journal impact factor.

As depicted in Table 5, the dependent variable is the target journal impact factor (*Target JIF*), and the independent variable is *Academic influence*. In Column 1, only *Academic influence* is included, whereas in Column 2 all relevant control variables are incorporated. Among junior authors, the coefficient for *Academic influence* is statistically insignificant ($p > 0.1$). These findings contradict the expected journal effect, indicating that there is no significant relationship between author academic influence and the target journal's impact factor among junior authors.

4.3.2. *Gender or home effect*

In this section, we examine whether the impact of author academic influence differs between male and female researchers (Ersoy and Pate 2023) and investigate the presence of home bias (Rubin, Rubin, and Segal 2023). As shown in Table 6, Columns 1 and 2 control for the paper's short-term impact, whereas Columns 3 and 4 control for its long-term impact. In Columns 1 and 3, interactions between *Male* and *Academic influence* are introduced, and in Columns 2 and 4, interactions between *US* and *Academic influence* are included. The results indicate that both sets of interactions are statistically insignificant. Consequently, we conclude that there is no compelling evidence to support the contention that author academic influence operates differently by gender or home country.

Table 5. Regression results of journal impact factor and author academic influence (junior authors).

	(1) Single variable	(2) All variables
Academic influence (ln)	−0.197	−0.157
	(0.194)	(0.201)
Constant	14.446***	5.805*
	(1.230)	(3.189)
Observations	1334	1334
Adjusted R^2	0.00	0.13
YM	No	Yes
Control variables	No	Yes

" >1) Standard errors in parentheses. 2) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 6. The interactions between academic influence and male/US.

	(1) Gender	(2) Country	(3) Gender	(4) Country
Academic influence (ln)	0.026	0.084*	0.009	0.086*
	(0.072)	(0.047)	(0.074)	(0.048)
Short-term impact (ln)	0.496***	0.498***		
	(0.079)	(0.079)		
Long-term impact (ln)			0.711***	0.713***
			(0.079)	(0.079)
Male	−0.547	−0.097	−0.648	−0.111
	(0.526)	(0.142)	(0.538)	(0.145)
Male # Academic influence (ln)	0.074		0.089	
	(0.084)		(0.086)	
US	0.108	0.184	0.102	0.325
	(0.134)	(0.493)	(0.137)	(0.498)
US # Academic influence (ln)		−0.012		−0.036
		(0.079)		(0.079)
Constant	0.305	−0.070	0.106	−0.392
	(0.866)	(0.765)	(0.912)	(0.803)
Observations	1334	1334	1334	1334
loglikelihood	−769.51	−769.87	−745.79	−746.19
aic	1645.02	1645.74	1597.57	1598.38
bic	1920.41	1921.12	1872.96	1873.76
YM	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

" >1) Standard errors in parentheses. 2) *p < 0.1, **p < 0.05, ***p < 0.01.

4.3.3. *Signaling effect*

Table 7 presents the regression outcomes from Equations (2) and (3) for the subset of junior authors. In Column (1), we regress peer review outcomes on *Academic influence*, and the coefficient is positive and statistically significant at the 0.01 level. In Column (2), we examine the relationship between *Academic influence* and the paper's Short-impact, but the coefficient is not statistically significant. In contrast, Column (3) replaces the mediator with the paper's Long-impact, and the coefficient remains positive and statistically significant at the 0.05 level.

These findings suggest that author academic influence is not significantly associated with the short-term impact of their papers, which casts doubt on the alternative explanation that influential authors simply produce higher-quality research that is immediately more citable. Instead, the significant relationship between author influence and long-term impact points to a different mechanism: the reputational visibility of influential authors may enhance the downstream recognition of their work and facilitate acceptance decisions, consistent with a signaling effect in peer review (H3).

5. Discussion and conclusion

This study introduces a unique dataset comprising submitted manuscripts with peer review outcomes, offering a comprehensive exploration of factors associated

Table 7. Mediation analysis for junior authors.

	(1) Accept	(2) Short-impact	(3) Long-impact
Academic influence (ln)	0.088**	0.022	0.029**
	(0.036)	(0.013)	(0.015)
Male	−0.070	0.063	0.068
	(0.139)	(0.051)	(0.053)
US	0.137	0.061	0.062
	(0.131)	(0.050)	(0.053)
No. of authors	−0.002	0.026***	0.027***
	(0.008)	(0.005)	(0.005)
No. of references	−0.006	0.002*	0.002**
	(0.004)	(0.001)	(0.001)
No. of Pages	0.087***	−0.001	−0.000
	(0.020)	(0.001)	(0.001)
Target JIF	−0.046***	0.032***	0.031***
	(0.006)	(0.003)	(0.003)
Constant	0.714	1.639***	1.588***
	(0.711)	(0.238)	(0.241)
Observations	1334	1334	1334
loglikelihood	−790.55	−1602.44	−1673.12
aic	1683.10	3306.89	3448.24
bic	1948.09	3571.88	3713.24
YM	Yes	Yes	Yes

" >1) Standard errors in parentheses. 2) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

with these outcomes from the perspective of the Matthew effect. The primary focus of our investigation is on a key factor in the peer review process: author academic influence, with an emphasis on exploring its relationship with manuscript acceptance. In contrast to prior studies that highlight a significant association between paper citation impact and acceptance (Bornmann et al. 2010; Casnici et al. 2017), a novel contribution of our study is the revelation that author academic influence plays a substantive role in the peer review process.

Moreover, our analysis reveals that this relationship between author academic influence and manuscript acceptance is even more pronounced among junior researchers. We attribute this phenomenon to a signaling effect, suggesting that author academic influence serves as a long-term impact signal to journals and reviewers amid the inherent uncertainty regarding the characteristics of submitted manuscripts. Consequently, this signaling effect contributes to an increased probability of manuscript acceptance.

Furthermore, the findings related to the control variables also merit discussion. In contrast to earlier studies (Murray et al. 2018), our analysis did not reveal substantiating evidence for gender or home bias. More evidence should be provided to reveal the gender and/or home bias in peer review.

This study contends that author academic influence can function as an informal seal of approval, reducing information asymmetry. However, it is crucial to acknowledge that author academic influence may contribute to inequality in the scientific landscape (DiPrete and Eirich 2006; Horta 2022; Melo, Joana, and Sandra 2019). Actually, within the tenure system paradigm, apprehensions have been expressed regarding a predilection for "glamorous" affiliations, potentially leading academic institutions to misjudge the true scholarly capabilities of prospective employees (Gerhards and Hans 2013; Schröder, Lutter, and Habicht 2021).

Additionally, the signaling effect could lead to unintended consequences. As more researchers compete to coauthor with well-know scientists or signal prestige through institutional ties, the value of these signals may erode. This competitive dynamic can disadvantage research teams lacking established reputations, making it harder for them to gain recognition in the peer review process. To foster an effective scientific institutional framework, it is imperative to evade a scenario where every individual seeks to overprove their worth. Moreover, in instances where the influence of authors' academic influence is inevitable, the implementation of open peer review, wherein reviewers and their comments are made public, can act as a form of oversight, potentially ameliorating inequalities within the system.

Our findings raise important ethical and policy concerns about bias and fairness in the peer review process. When academic influence consistently increases the likelihood of acceptance, it challenges the objectivity of evaluations. To protect fairness, journals should implement safeguards such as transparent editorial criteria, clear review guidelines, and explicit reflection on how author-related factors are weighted. Future research and policy efforts should explore how to balance the efficiency of expert-based assessments with equitable treatment of less-established scholars.

Finally, while our study identifies a significant relationship between author academic influence and manuscript acceptance, establishing a definitive causal link remains a challenge, particularly because manuscript quality is inherently difficult to measure and isolate. Nevertheless, our analyses show no significant association between author influence and short-term paper impact, suggesting that academic influence may not merely reflect higher-quality research. Given the comprehensive set of controls incorporated into our models, we believe this concern may be less pronounced than it initially appears. Moreover, by focusing only on accepted manuscripts, we may underestimate the full extent of the Matthew effect, as some submissions by less prominent authors may have been rejected and thus remain unobserved in our dataset. Accordingly, our estimates likely represent a lower bound on the influence of author academic standing in the peer review. While our models assume a linear relationship between academic influence and acceptance, we acknowledge that future research could explore potential nonlinearities or threshold effects – particularly across author seniority levels or journal types – to better understand the boundaries of the observed patterns.

Taken together, our findings highlight the dual role of academic influence in peer review – as both a signal of potential and a source of inequality. Future efforts to improve peer evaluation should recognize this tension and design systems that reward scholarly merit without reinforcing structural biases.

Our study is subject to several limitations. First, the data come exclusively from Cell Press journals, which publish high-impact research in biology. These findings may not generalize to other disciplines or journals with different review norms. Secondly, we used Google-based methods to track manuscript submissions, which, while validated by prior work (Casnici et al. 2017; Schroter et al. 2022), may miss some records due to incomplete digital trace. Third, our analysis defines "peer review outcomes" as editorial decisions following reviewer input, but we cannot separately identify the roles of reviewers and editors. Finally, factors such as efforts to promote emerging topics or support diversity, equity, and inclusion (DEI) may also influence acceptance decisions. However, these elements are beyond the scope of our data and therefore cannot be directly incorporated into our empirical analysis.

Notes

1. A description of the website of SSRN Paper is provided in the supplementary materials.
2. The rationale for excluding unpublished manuscripts is detailed in the supplementary materials.
3. A comparison of citation counts between first and last authors in our dataset is presented in the supplementary materials.

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