Learning by Evaluating:
Evidence from Academic Peer Review

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Abstract

The evaluation of innovative projects is an essential task for scientific and business organizations alike. While prior work has focused on the quality of evaluations and how they affect innovators, little is known about how the evaluation process affects evaluators themselves. We propose that evaluations provide evaluators with valuable learning opportunities by exposing them to relevant, cutting-edge knowledge. We test the argument in the setting of academic peer review, using administrative data from the Institute of Physics Publishing comprising 104,306 reviewer-manuscript pairs across 55 physical sciences journals. We find that evaluating a manuscript more than doubles the likelihood of a reviewer using that knowledge (by citation) within three years compared to qualified evaluators who were invited but unavailable. Evaluators' geographic and intellectual distance to the work moderates the learning effects of evaluation. While unavailable evaluators from the same country as a paper's corresponding author have significantly higher baseline citation rates, evaluators from different countries who reviewed the paper achieved similarly high citation levels, indicating that structured evaluation of external ideas can compensate for geographic boundaries in knowledge transfer. Intellectual proximity between evaluators' recent work and the work being evaluated is associated with stronger learning effects. These findings show that expert evaluations benefit not only organizations (by improving resource allocation) but also the evaluators themselves, which helps explain why they participate in the laborious and seemingly under-incentivized work.

Keywords: Peer review, knowledge spillovers, geographic proximity, scientific collaboration, absorptive capacity

1. Introduction

Allocating resources is a core task for individuals and organizations. Whether in funding agencies, business firms, research institutions, or government bodies, the ability to identify and support promising opportunities from a pool of competing alternatives directly shapes an organization's innovation trajectory, competitive position, and long-term viability (Stephan, 2012; Criscuolo et al., 2017; Lane et al., 2022). In science, this allocation takes various forms, from determining which manuscripts deserve limited journal space and associated reputational benefits to which research proposals warrant scarce funding. The efficiency and effectiveness of these allocation decisions fundamentally influence the pace and direction of scientific progress in our knowledge economy (Azoulay and Li, 2020; Myers, 2020).

To accomplish this critical function, organizations increasingly rely on evaluation systems that leverage expert judgment to assess the quality, potential, and fit of proposals, projects, or manuscripts (Boudreau et al., 2016; Erosheva et al., 2021). From hiring decisions and R&D project selection to venture capital investments and scientific peer review, expert evaluation has become a ubiquitous mechanism underpinning diverse organizational processes. The implicit assumption is that expert evaluators provide unique insights that improve allocation decisions, thus justifying the substantial resources dedicated to these assessment systems (Li, 2017).

Yet these evaluation processes create an interesting paradox: while they benefit organizations through improved resource allocation, the review process often goes unrecognized and is viewed primarily as a burden by the experts themselves (Bendiscioli, 2019). The mounting demand for experts' judgment is particularly alarming given growing concerns about "reviewer fatigue" in scientific publishing (Fox et al., 2015; Kovanis et al., 2016; Vesper, 2018). Peer review imposes considerable demands on evaluators' time and cognitive resources. Resources that early-career researchers could otherwise devote to publications, grants, and other activities directly rewarded in tenure and promotion decisions (Franzoni, Scellato, and Stephan, 2011; Stephan, 1996; Walton, 2019). Given these pressures, many organizations are exploring ways to reduce reliance on expert evaluators, with some even considering automated

alternatives such artificial intelligence powered evaluations (Lane et al., 2024; Doshi et al., 2024). While AI-based solutions offer promising efficiency gains, they also introduce substantial uncertainties around quality and reliability of evaluations. More importantly, the rush toward automation may overlook a critical dimension of the peer review process: its potential role as a knowledge acquisition channel with valuable spillover benefits for reviewers. Survey evidence suggests that only 6% of reviewers believe the process enhances their professional credentials, with most citing intrinsic motivations (Walton, 2019). However, the persistence of reviewer participation despite minimal formal incentives hints at unrecognized benefits beyond relational contracting, editor relationships, and altruism (Engers and Gans, 1998; Griffin and Barczak, 2020; Squazzoni et al., 2013), benefits that may include learning opportunities.

Hence, we address this puzzle by investigating peer review as a knowledge acquisition channel with significant evaluation knowledge spillovers. Our approach conceptualizes peer review as a structured commitment device that "forces" reviewers to engage deeply with new material (Bryan, Karlan, and Nelson, 2010), similar to how conferences facilitate focused engagement (Teplitskiy et al., 2023). This commitment likely yields substantial learning benefits that extend beyond altruistic or reputational incentives, potentially addressing a key gap in our understanding of knowledge flow mechanisms in scientific communities (Murray & O'Mahony, 2007). Our study addresses three central questions: (1) Does reviewing a manuscript increase the likelihood of knowledge acquisition, as evidenced by subsequent citations? (2) How does geographic distance moderate this relationship, i.e., does reviewing compensate for or reinforce existing knowledge flows across spatial boundaries? (3) Does the intellectual distance between a reviewer's expertise and the manuscript's content influence the magnitude of learning?

With these questions we posit a knowledge acquisition through peer review that is not uniformly distributed across all evaluator-evaluated relationships. The efficacy of this learning channel likely depends on two critical dimensions of distance between reviewer and manuscript. First, intellectual distance, the degree of overlap between the reviewer's expertise and the manuscript's subject matter,

may influence knowledge acquisition dynamics (Leahey, Beckman, and Stanko, 2017). Greater distance potentially exposes reviewers to non-redundant knowledge that stimulates creativity (Jeppesen and Lakhani, 2010), while minimal distance may limit novel learning opportunities. That said, we recognize that greater intellectual distance creates a tension: while it may expose reviewers to more novel content, it likely produces higher variance in scientific utility and provides fewer opportunities for reviewers to deploy this knowledge in their own work. Second, geographic distance may shape knowledge transfer during review in ways that complement or substitute for other knowledge diffusion mechanisms. Reviewers from different regions bring diverse contextual experiences that could enhance their understanding and integration of new ideas (Catalini et al., 2020). Geographic separation often correlates with differences in institutional cultures, methodological approaches, and research priorities, all of which might enrich the reviewer's learning experience (Breschi and Lissoni, 2009). These distance effects may be particularly important in determining how knowledge flows through structured evaluation processes across organizational and geographic boundaries (Lane & Maxfield, 1996).

To empirically test these relationships, we leverage administrative data from 55 physical sciences journals published by the Institute of Physics and employ an innovative identification strategy. Our analysis compares reviewers who completed evaluations with qualified individuals who were invited but unavailable, hence providing a useful setting to estimate to what extent reviewing is associated with knowledge acquisition. This approach reveals that reviewing a manuscript more than doubles the likelihood of citing it within three years suggesting strong evidence of knowledge acquisition. Moreover, both geographic and intellectual proximity moderate this effect. While reviewers from the same country as the manuscript's authors show higher baseline citation rates, the act of reviewing partially compensates for barriers imposed by geographic distance. The treated "far" group (distant reviewers who evaluated the manuscript) achieves citation levels similar to the control "close" group (proximate reviewers who did not evaluate). Similarly, intellectual proximity (measured through abstract similarity) demonstrates a positive baseline effect, with reviewing amplifying this relationship.

These findings contribute to several important research streams with implications for both theory and practice. First and foremost, they reveal a previously underappreciated private benefit of evaluating, the opportunity to learn, which helps explain the paradox of continued participation in seemingly under-incentivized review activities. This informs the literature on contributions to public goods by identifying a concrete non-altruistic benefit that helps address concerns about reviewer fatigue. It also enriches our understanding of evaluation processes in innovation by highlighting benefits beyond resource allocation. Second, the effects vary with geographic and intellectual distance, informing the literature on geography and knowledge diffusion by demonstrating how formal evaluation processes can partly overcome spatial barriers to knowledge transfer. It also contributes to research on absorptive capacity by showing how intellectual proximity enhances learning benefits, supporting the importance of prior related knowledge in effectively assimilating and applying new information.

The remainder of the paper proceeds as follows. Section 2 develops our theoretical framework and formal hypotheses. Section 3 describes our research design and empirical approach. Section 4 details the variables and provides descriptive statistics. Section 5 presents our findings, and Section 6 concludes with discussion and implications for theory and practice.

2. Theoretical Framework and Hypotheses

2.1 Knowledge Acquisition Through Peer Review

Prior work suggests that scientific discovery is a process that may arise through multiple pathways, such as interactions with other researchers, experimentation, reading published work, applying to grants, or attending seminars and conferences (Boudreau and Lakhani, 2015; Dahlander and McFarland, 2013; Ayoubi et al., 2019; Lane et al., 2020; Teplitskiy et al., 2023). Consequently, we can expect peer evaluation to be an alternative pathway through which individuals are exposed to new ideas that can be absorbed, learned, and integrated into their own research, and may result in knowledge transfer.

A key insight in investigating when encounters with novel ideas will affect innovative potential is acknowledging that exposure is only half the story; the other half requires integrating and applying new

knowledge with one's own experiences and expertise (Argote, 2012; Argote and Ingram, 2000; Bresman, 2010). It is only after both of these stages have been carried out effectively that learning has occurred (Argote, 2012; Argote and Ingram, 2000; Huber, 1991). This process is often evidenced by knowledge recombination (Fleming, 2001; Schilling and Green, 2011; Weitzman, 1998). Knowledge recombination involves the movement of facts, relationships, ideas and insights from one setting to another, and becomes evident when the experience acquired by an individual, group or firm in one setting is *integrated* into another setting (Argote, 2012; Hansen, 1999; Szulanski, 1996). Much research has conceptualized knowledge transfer and integration as a two-sided process that depends on the source's willingness to share knowledge with a recipient and the recipient's efforts to acquire, absorb and integrate it with their existing knowledge bases (Argote, 2012). Hence, the process of knowledge transfer tends to be difficult to facilitate effectively and suggests that, even when individuals are exposed to diverse information and new ideas, they may fail to acquire the knowledge and integrate it effectively with their existing knowledge base (Carlile, 2004; Kogut and Zander, 1992).

There are two channels through which exposures to new ideas can lead to knowledge transfer. The first channel is through personal interactions or direct contact, such as face-to-face, phone or video conference (Hansen, 1999; Reagans and McEvily, 2003, 2003; Uzzi, 1997). These personal interactions occur when one person shares advice or information with another individual and they are often informal in nature (Haas and Hansen, 2007). Although these types of interactions are important for developing social relations between people (Uzzi, 1997; Uzzi and Spiro, 2005), one drawback is that because the messages are in real-time and simultaneous, the communication is fleeting and cannot be reviewed and revisited (Clark and Brennan, 1991). Hence, these types of interactions may lead to shallower knowledge transfer because the ideas, insights and advice exchanged are typically not recorded and cannot be reviewed after the initial encounter and exchange. The second channel is through exposure to the ideas contained in written documents (Haas and Hansen, 2007), and is the focus of our study. Written documents play an essential role in knowledge sharing within organizations, and are an important way through which individuals are exposed to diverse information and ideas. Knowledge workers often disseminate what they know in writing, such as in presentations, policies, tutorials, and upload these

documents into databases or document management systems that can then be accessed by third parties (Haas and Hansen, 2007). A key advantage of written documents is that the communication is persistent and remains accessible in the same form as the original display for others to search, browse, annotate, visualize, structure and recontextualize (Erickson and Kellogg, 2000). Whereas verbal communication fades quickly, written documents stay behind as an artifact that can be reviewed later by any individual (Clark and Brennan, 1991). For example, Jeff Bezos, the long-time Amazon CEO, has famously instilled a culture of written documents before important meetings. In particular, rather than brainstorming ideas, Amazon executives are asked to submit six-page, dense, narratively structured memos of their novel ideas that each senior leader reads prior to starting a discussion (Bashaw, 2019). While both verbal and written communication channels have their merits, what's most critical for knowledge transfer in evaluation contexts is the depth of engagement with novel ideas.

Evaluation processes are particularly powerful because they require evaluators to move beyond passive consumption of content to active critical assessment. When evaluating manuscripts, reviewers must thoroughly understand the work's arguments, methods, and implications, analyze its contributions relative to existing knowledge, and form reasoned judgments about its validity and importance. This structured, deliberate engagement creates cognitive conditions that are especially conducive to knowledge absorption and integration, regardless of the specific medium through which the ideas are conveyed. In academic peer review specifically, the responsibility of providing constructive feedback further incentivizes deep engagement with the material, potentially enhancing learning outcomes beyond what might occur through casual reading or conversation. This engaged, critical interaction with novel ideas helps establish common knowledge and beliefs between the evaluator and the knowledge creator, and has been shown to improve the transmission of complex ideas (Clark and Brennan, 1991), such as new scientific concepts. These reasons suggest that evaluations of novel ideas, embodied in scientific articles, are likely to facilitate exposure to diverse ideas that leads to successful knowledge transfer outcomes.

In academic science, written documents are an important means through which knowledge is disseminated, as evidenced by the vast volume of scientific material published each year (Stephan, 2012). Integral to this process is the role of evaluations in scrutinizing the knowledge claims of others in the field, and is understood as providing "a system of institutionalized vigilance" where evaluators provide an impartial and fair interpretation of the submitted work (Merton, 1973). There are two milestones in the progression of a scientific idea that typically involves formal evaluations by experts. The first is for prospective evaluations of early-stage ideas, which entails decisions of whether to support them for funding and further development (Ayoubi, Pezzoni, and Visentin, 2019; Boudreau *et al.*, 2016; Li, 2017). The second is for submitted manuscripts which undergo retrospective evaluations of completed manuscripts prior to publication (Blank, 1991; Cicchetti, 1991). We argue that prospective evaluations of novel scientific manuscripts submitted to journals create unique opportunities for exposure to diverse ideas.

The knowledge embodied in scientific articles, namely novel ideas, is by definition, comprised of new research that aims to extend the current state of knowledge beyond the current knowledge frontier (Boudreau *et al.*, 2016). This suggests that the novel nature of the ideas contained in papers makes them well-suited for idea exposures that may eventually lead to successful knowledge transfer. In particular, studies on creativity and innovation suggest that people's initial ideas are often not the most innovative ones, because people tend to default to prior experiences when coming up with their earliest ideas. Hence, it is only after these preliminary ideas have been exhausted that more promising ideas emerge (Ward, 1994). This creates opportunities for evaluators to not only absorb and acquire new ideas, but also reuse, reshape, refine and combine them into their own work. Therefore, we hypothesize:

Hypothesis 1 (H1): Reviewers acquire new knowledge through the evaluation of submissions, as evidenced by an increased likelihood of citing reviewed papers in their subsequent publications.

As firms and individuals search for new knowledge, both local searches that concentrate narrower domains and distant searches spanning more diverse domains can lead to encounters with novel ideas. Hence, beyond the role of exposure to new ideas on knowledge acquisition, it is essential to understand

how encounters with novel ideas in both local and distant searches for new knowledge affect knowledge acquisition, to gain deeper insight into the innovation process. In other words, it is critical to consider the impact of the geographical as well as the intellectual distance between the firm or individual's domain of expertise and the focal domain of the idea on knowledge acquisition.

In the remainder of this section, we theorize when exposure to diverse information sources will lead to knowledge transfer. More specifically, we theorize how two factors shape whether encounters with novel ideas are likely to result in knowledge recombination: the national proximity of the producer and evaluator, and the intellectual distance between an individual's expertise and the domain of the article evaluated.

2.2 The Moderating Role of Geographic Distance

Having established that peer review can serve as a mechanism for knowledge acquisition in Section 2.1, we now examine how the effectiveness of this channel varies with geographic distance between reviewers and manuscript authors. While the structured engagement of peer review may facilitate knowledge transfer broadly, the magnitude of this effect likely depends on pre-existing knowledge access pathways that differ systematically by geography. Geographic proximity has long been recognized as a catalyst for knowledge spillovers across organizations, institutions, and individual researchers (Jaffe, Trajtenberg, & Henderson, 1993; Audretsch & Feldman, 1996; Singh, 2005). Unlike the formal, structured knowledge transfer that occurs during peer review, proximity enables numerous informal pathways, such as frequent face-to-face interactions, casual encounters, and participation in local knowledge networks, that facilitate the spontaneous transmission of both codified and tacit knowledge (Maskell & Malmberg, 1999; Storper & Venables, 2004; Howells, 2002). These informal, geography-based knowledge flows operate through multiple complementary channels. Co-location reduces coordination costs and travel time, increasing the frequency of in-person exchanges (Catalini, 2018; Rawley & Seamans, 2015) that facilitate the transmission of complex, tacit knowledge resistant to codification in written documents (Roche, 2020). Shared regional contexts foster common understanding and interpretive frameworks that ease knowledge assimilation (Saxenian, 1996; Gertler, 2003), while local professional networks

create redundant information pathways that increase serendipitous exposure to relevant work (Powell, Koput, & Smith-Doerr, 1996; Owen-Smith & Powell, 2004). These mechanisms collectively ensure that scientists are typically more aware of, and more likely to learn from, research conducted in their immediate geographic vicinity, independent of formal review processes (Breschi & Lissoni, 2009; Almeida & Kogut, 1999). Recent research provides compelling causal evidence for these geographic effects. Roche (2020) demonstrated that geographic proximity uniquely benefits knowledge recombination as inventors relocating to innovation hubs experienced significant increases in combinatorial novelty by accessing locally embedded knowledge that facilitated unexpected connections between previously separate domains. Even within single institutions, the microgeography of physical space shapes knowledge flows. Catalini (2018) showed that relocating scientists to different floors within the same building dramatically reduced their collaboration likelihood, while moves to adjacent spaces increased collaborative activities. These findings indicate that informal knowledge spillovers remain highly localized even within institutional boundaries. For geographically proximate reviewers and authors, these overlapping informal channels create significant redundancy in knowledge access pathways. Proximate reviewers may encounter authors' work through local seminars, institutional repositories, pre-publication workshops, or mutual collaborators (Boudreau et al., 2017; Ganguli, 2017) long before formal review processes begin. Shared cultural contexts and institutional norms further reduce barriers to knowledge absorption (Phelps, Heidl, & Wadhwa, 2012). As a result, reviewers from the same geographic region as manuscript authors likely possess higher baseline familiarity with the research content before any formal review begins. In stark contrast, geographically distant reviewers typically lack these abundant informal exposure channels. Without the structured engagement provided by peer review, they might never encounter, or deeply engage with, research from distant researchers (Bell & Zaheer, 2007; Cummings & Kiesler, 2007). For these distant reviewers, the formal review process serves as a crucial bridge across geographical divides, providing access to knowledge that might otherwise remain less accessible (Agrawal, Kapur, & McHale, 2008; Fleming, King, & Juda, 2007). While geographically proximate reviewers can draw on multiple redundant information sources, distant reviewers often have the peer review process as an important channel for

exposure to specific research developments from other regions (Kotha, George, & Srikanth, 2013; Tortoriello, Reagans, & McEvily, 2012). This fundamental disparity in baseline knowledge access suggests a key interaction effect between the review process and geographic distance. While reviewing likely increases knowledge acquisition for all evaluators compared to non-reviewing, the marginal information gain should be systematically larger for geographically distant reviewers who lack alternative exposure pathways (Broekel & Boschma, 2012; Laursen, et al., 2011). In essence, peer review may serve as a partial substitute for the knowledge access advantages that geographic proximity typically provides (Roche, 2020; Catalini et al., 2020), with distant reviewers having "more to learn" from the structured engagement with manuscripts outside their geographic reach. Conversely, local reviewers already embedded in overlapping knowledge networks with authors may experience relatively smaller learning increments from the formal review process (Boschma, 2005; Torre & Rallet, 2005). For these proximate reviewers, the manuscript content may contain fewer genuinely novel elements, as they may have already absorbed key ideas through their rich local information environment. Thus, while they still benefit from the structured engagement that peer review provides (as argued in Hypothesis 1), the magnitude of this benefit should be relatively smaller compared to that experienced by distant reviewers. Recent empirical evidence supports this differential effect across various structured knowledge exchange contexts. Boudreau et al. (2017) documented how structured research symposia produced greater collaboration benefits for previously unconnected researchers. Roche et al. (2024) further demonstrated that temporary colocation at technology coworking hubs yields disproportionate knowledge transfer benefits for scientists working in less connected institutions. One can therefore expect that exposure to certain knowledge through reviewing will be reinforced by the closer geographical distance with the source of the knowledge. These effects should be even greater given other aspects of national proximity such as common institutional norms, scientific systems, language and social networks. However, on the absolute scale, the repeated exposure for geographically close reviewers as well as their initial proximity could also lead to higher absolute learning by reviewing effect.

Building on these theoretical foundation and empirical evidence, we propose that the knowledge acquisition benefits of peer review (established in Hypothesis 1) will vary systematically with geographic

distance. The "learning-by-reviewing" effect should be relatively stronger for reviewers who are geographically proximate to manuscript authors, as they start with higher baseline knowledge access through multiple informal channels. This leads to our second hypothesis:

Hypothesis 2 (H2). Reviewers from a different country than the manuscript's authors experience a larger relative but a smaller absolute increase in subsequent citations than do reviewers from the same country.

2.3 The Moderating Role of Intellectual Distance

Having established the role of geographic distance in moderating knowledge acquisition through peer review, we now turn to a second critical dimension: intellectual distance, i.e. the cognitive gap between a reviewer's expertise domain and a manuscript's content. While geographic proximity facilitates knowledge access through physical channels, intellectual proximity shapes the cognitive processes involved in recognizing, assimilating, and applying new knowledge from manuscripts.

When reviewers evaluate manuscripts closely aligned with their expertise, cognitive proximity enables rapid comprehension of specialized terminology, methodological approaches, and theoretical foundations (Lane & Lubatkin, 1998; Reagans & McEvily, 2003). This familiarity reduces absorption costs and facilitates integration of new insights into existing knowledge structures. Cohen and Levinthal's (1990) work on absorptive capacity emphasizes that prior related knowledge enhances the assimilation of new information, suggesting that domain experts could more efficiently integrate novel contributions from manuscripts. However, cognitive proximity also creates potential limitations for learning. When reviewers possess knowledge bases highly similar to manuscript authors, they may encounter fewer genuinely novel elements worth adopting. Low cognitive distance entails similar knowledge stocks and thus the probability of learning if there is too little novelty to learn from (Ayoubi et al., 2017). This redundancy effect potentially diminishes the marginal knowledge gain from review activities (Wuyts et al., 2005; Van Wijk, Jansen, & Lyles, 2008).

Conversely, extensive research on creativity highlights the generative potential of cognitive distance. When reviewers encounter manuscripts from adjacent domains, they gain exposure to non-redundant

knowledge that may complement their existing expertise in unexpected ways (Hargadon & Sutton, 1997; Fleming, 2001). This exposure can trigger novel associations and recombinations that might not occur within their primary field (Amabile et al., 2005; Perry-Smith & Mannucci, 2017). Studies of breakthrough innovations consistently find that many originate at the intersection of distant knowledge domains (Powell, Koput, & Smith-Doerr, 1996; Uzzi et al., 2013). Yet excessive cognitive distance introduces comprehension barriers. When the gap between reviewer expertise and manuscript content becomes too large, reviewers may struggle to understand fundamental concepts, potentially hampering effective knowledge transfer (Zhou & Li, 2012; Piezunka & Dahlander, 2015). Cognitive load theory suggests that learning efficiency decreases when individuals must simultaneously master numerous unfamiliar concepts (Sweller, 1988; Paas, Renkl, & Sweller, 2003).

These competing mechanisms—enhanced novelty versus diminished comprehension—create a theoretical tension characterized by two countervailing effects: the "speaking the same language" effect that enhances knowledge flows when cognitive distance is low, and the "opening new horizons" effect that has a positive impact as cognitive distance increases (Ayoubi et al., 2017). Similar patterns emerge across multiple innovation contexts. Rosenkopf and Nerkar (2001) found that patents combining moderate technological distance yielded greater impact than those at either extreme. Fleming (2001) documented parallel findings in inventor productivity, with moderate knowledge recombination distance producing the most valuable innovations. In scientific evaluation, Boudreau et al. (2016) observed that reviewers responded most positively to proposals of intermediate novelty.

The peer review process introduces a unique dynamic to this relationship. Unlike established knowledge domains, manuscripts under review represent unpublished frontier research containing novel elements not yet in the mainstream literature. This inherent novelty partially mitigates redundancy concerns present in other knowledge exchange contexts. Even when reviewers possess substantial domain expertise, manuscripts likely offer new findings, methods, or theoretical extensions worth adopting. This distinctive characteristic suggests that while extreme intellectual distance may still impede learning

through comprehension barriers, the redundancy risks at low intellectual distances are somewhat attenuated in peer review.

Building on these theoretical foundations and empirical evidence, we propose that the knowledge acquisition benefits established in Hypothesis 1 will be moderated by intellectual distance between reviewer and manuscript, with intellectual distance having a positive interaction on learning given that intellectually similar reviewers possess sufficient domain knowledge to comprehend the manuscript while still encountering novel elements that stimulate innovative recombinations. Given these theoretical considerations and empirical precedents, we posit:

Hypothesis 3 (H3). Intellectual distance between a reviewer's prior expertise and the manuscript negatively moderates the learning-by-reviewing effect. Reviewers with a high intellectual similarity to the manuscript being evaluated experience stronger knowledge gains than do those with low intellectual similarity.

3. Methodology

Having established our theoretical framework on how evaluating affects knowledge acquisition and the moderating roles of geographic and intellectual distance, we now detail our empirical approach to testing these hypotheses. This section outlines our data collection process, variable construction, and analytical strategy.

3.1 Data Collection

Our study utilizes administrative data from an initial set of 62 Institute of Physics Publishing (IOP) journals, covering 229,173 manuscript submissions between 2018-2022. We implemented a multi-stage sample selection process to construct a dataset suitable for analyzing learning dynamics in peer review (see Figure 1). Data from IOP was then matched to records in OpenAlex, a comprehensive, open index of scholarly works (Priem, Piwowar, & Orr, 2022), to construct several key variables.

First, we restricted our sample to include only manuscripts that (1) underwent at least one round of peer review (e.g., desk rejections excluded), (2) were submitted during 2018-2019 to avoid potential COVID-

19 confounding effects while ensuring sufficient post-publication citation windows, and (3) were eventually published, either in IOP journals or elsewhere. For IOP-published papers (71,123 submissions), we used the DOI provided in the dataset to locate them directly in the OpenAlex database. For papers rejected from IOP but published elsewhere (93,605 submissions), we employed a two-step identification process employed in prior work (Chen et al., 2024). To link these rejected submissions to OpenAlex records, the first step involved creating an inclusive group of candidate records from the publications of all authors on a submission. If authors provided an ORCID, their record was located directly, otherwise author full name and a combination of author last name with country and field information were used for search. The second step involved the use of a logistic classifier trained on survey data (Chen et al., 2024) where submitting authors reported any name changes to their rejected submission. This two-step process achieved 97% precision and 78% recall in identifying published papers among candidate publications.

Second, for each submission, we collected the OpenAlex records of all works that cited the published version as of January 2025 ("citing works"). Submissions that received no citations were removed from the sample. Crucially, this step gathered full author lists for each citing work.

Third, to identify reviewers in the OpenAlex database, we followed a systematic approach. Some reviewers provided an ORCID, allowing for direct location. For reviewers without an ORCID in our data, we conducted a search using institution name plus reviewer full name when institution data was available and found in OpenAlex. If institution data was missing or not found in OpenAlex, we resorted for reviewer full name search only. Searches specified the Physics concept tag to restrict results to relevant fields. We retained the first search result when fewer than 25 potential matches were found and excluded cases with too many potential matches (labeled "Too many authors found") or no matches ("No OA author found"). This process allowed us to collect productivity metrics as of January 2025 for 69,627 unique reviewers across 388,311 reviewer-manuscript pairs.

Finally, we included only invited reviewers who either (1) agreed to the invitation and completed a review (treatment group) or (2) declined the invitation explicitly stating they were unavailable (control

group). Other responses not included in the final analytic sample include those who did not respond to invitation, those who had an auto-declined on,[1] and those who explicitly declined for other reasons (e.g., conflict of interest, out of field). This restriction is crucial for our identification strategy, as unavailable reviewers represent a plausible counterfactual—qualified individuals who would have reviewed the submission but could not due to exogenous time constraints. In sum, this approach yielded a sample of 104,306 reviewer-manuscript pairs for 45,435 unique submissions to 55 journals for our primary analysis.

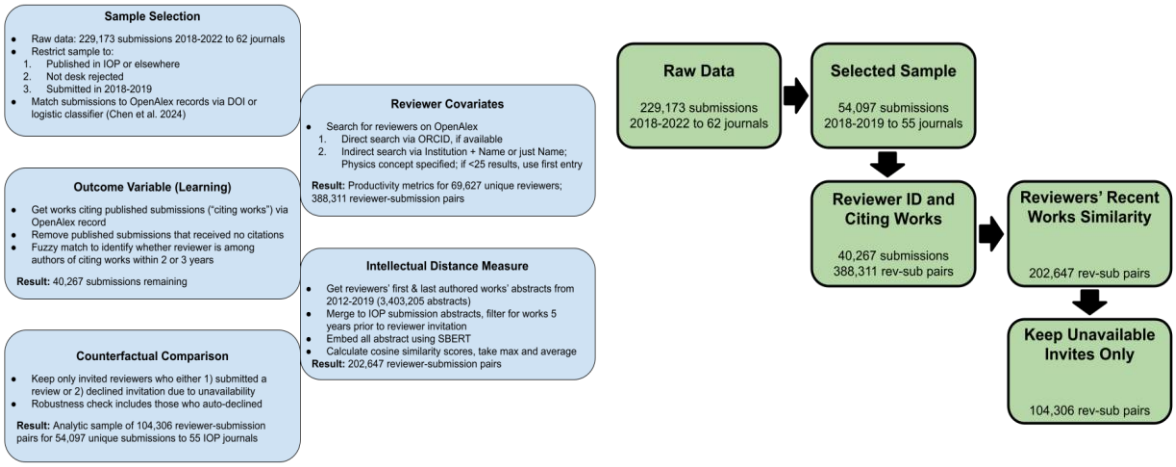


Figure 1: Data collection and cleaning process

3.2 Measurement of Variables

3.2.1 Dependent Variable: Learning

Our primary dependent variable is a binary indicator of reviewer learning, equal to 1 if the reviewer cited the manuscript they were invited to review in their subsequent work within three years, and 0 otherwise. This operationalization aligns with our theoretical framework, where citation behavior serves as a proxy for knowledge acquisition and integration.

To construct this variable, we restricted each submissions list of citing works to only keep those within three years of the reviewer's invitation. Then, reviewer names were fuzzy-matched to authors of the

[1] Note that we consider this sample as control for robustness check in Appendix.

citing works using a Levenshtein distance threshold of 80. A similar process was used with a two-year window and to generate counts instead of binaries for later robustness checks.

3.2.2 Independent Variable: Review Completion

Our key independent variable is a binary indicator of review completion (see Appendix for full list of responses). It equals 1 if the reviewer agreed to and completed the review, and 0 if they declined due to unavailability. More specifically, this variable is set to 1 if the reviewer's response is "Agreed". It is set to 0 if the reviewer's response is "Declined – Unavailable." This variable allows us to test Hypothesis 1 on whether reviewing a manuscript increases the likelihood of subsequent knowledge acquisition.

3.2.3 Moderating Variables

Geographic Distance

To test Hypothesis 2 on the moderating role of geographic proximity, we constructed a binary variable indicating whether the reviewer and the manuscript's corresponding author are from the same country. Countries are auto-filled from the self-reported institution of reviewers and authors. We compared the country codes of the reviewer and the corresponding author, assigning a value of 1 when they matched, indicating geographic proximity, and 0 if they did not match. Most authors and reviewers in our data are from the USA, China, and India, but a total of 139 countries are represented in our analytic sample.[2]

Intellectual Distance

To test Hypothesis 3 on the moderating role of intellectual proximity, we developed a sophisticated measure comparing the semantic similarity between submission abstracts and reviewers' recent publication abstracts. First, abstracts of submissions were already included in the IOP data. Reviewers'

[2] While acknowledging that same-country matching represents a coarse measure of geographic distance—researchers near borders may be physically closer to foreign colleagues than to distant compatriots—this approach still captures many proximity-related mechanisms relevant to knowledge flows, including shared institutional contexts, language, and research networks.

OpenAlex records were used to collect records of their first and last-authored publications from 2012-2019, totaling 3,403,205 abstracts for 69,627 unique reviewers.

Second, for each reviewer-submission pair, the reviewer's abstracts were filtered to include only those from the five years prior to their invitation (e.g., 2013-2017 if reviewer was invited in 2018). This operationalizes a comparison targeting reviewers' recent work that is not influenced by reviewing.

Third, all abstracts (submission and reviewer's) are transformed into embeddings using the Sentence Transformers (SBERT) "all-mpnet-base-v2" model (Reimers & Gurevych, 2019). Embedding models fine-tuned for scientific text are often trained using citation networks and thus are less appropriate for our analysis of citation likelihood than more general models like SBERT.

Last, cosine similarity scores were calculated for each submission abstract and the reviewer's eligible publication abstracts, resulting in each reviewer-submission pair having an array of similarity scores. From this array, the maximum similarity score is used as our primary measure of intellectual proximity representing the minimum distance between the evaluator and the object of evaluation. Higher values indicate greater cognitive overlap. The average of the similarity score arrays were also captured for robustness checks. This procedure resulted in 202,647 reviewer-manuscript pairs with intellectual distance measures.

3.2.4 Control Variables

We included several control variables to account for factors that might influence citation patterns:

- *Team Size*: The number of authors on the manuscript submitted.
- *Submission Year*: Extracted from the submission date information to account for temporal dynamics.
- *Journal Fixed Effect*: Controls for unobserved heterogeneity at the journal level.
- *Manuscript Fixed Effect*: Controls for unobserved heterogeneity at the manuscript level including topic and quality. Use of manuscript fixed effects absorbs other controls like team size and submission year, as these do not vary within-manuscript.

- *Reviewer Productivity Measures*: Including counts of publications and citations, h-index, and i-10-index. Metrics are binned into deciles for deidentification purposes.[3]

3.2.5 Other Variables

To further validate our findings and address potential alternative explanations, we constructed several additional measures for robustness checks:

Co-authorship Pre- and Post-treatment: Another alternative reviewer learning measurement we explored was co-authorship between the reviewer and the corresponding author of the reviewed manuscript before and after reviewer invitation. The pre- and post-treatment periods were defined as the reviewers' publications five years before and three years after their invitation to review. For each period, we concatenated the author lists of each of the reviewers' publications into a single list of co-authors. Then, we fuzzy-matched the names in this list to the name of the corresponding author of the reviewed manuscript using a Levenshtein distance threshold of 80. Binary and count versions of this variable were captured. Note that our analytic sample excluded reviewers who declined due to a conflict of interest, such as previous co-authorship.

Reviewer Publications Post-treatment: To address potential confounding by differential productivity, we examined whether the learning effects are driven by the most productive reviewers. Reviewers' publications three years after being invited to review were captured from OpenAlex, and reviewers were binned into tertiles (Low, Mid, and High post-treatment publications) for comparison.

Double-anonymous Submissions: Most IOP journals in 2018 and 2019 were single-anonymous, with author information visible to reviewers. However, five journals offered voluntary double-anonymization, allowing authors to hide their identities by submitting through a separate website. In these journals, 15% of submissions were anonymous. We used this subset to explore whether knowledge

[3] For the published dataset, we implemented a deidentification process that: 1) transformed journal abbreviation, manuscript ID, reviewer name, and country information into random 10-character strings and 2) binned identifying covariates (total citations, publications, h-index, team size) into 5 quantiles.

of author identity moderates reviewer learning, while acknowledging potential systematic differences between authors who chose anonymization (See Appendix B for the result on anonymization).

Reviewer Recent Publication in Journal: To address potential confounding by unobserved reviewer interest in the work, we constructed a measure of whether invited reviewers had recently published in the journal inviting them. Although actual reviewers and those who declined due to unavailability are similarly relevant to the manuscripts they were invited to review in terms of intellectual distance, it is possible that those with less interest selected into declining and used unavailability as an excuse. We used recent publication in the inviting journal as a proxy for interest, reasoning that reviewers who published in the venue recently are active members of that research community. We concatenated the publication venues of the reviewers' publications five years prior to invitation, then fuzzy-matched the names of these venues to the journal inviting them using a Levenshtein distance threshold of 80. Both binary and count variables were constructed for robustness checks.

3.3 Analytical Approach

We employ OLS regression models to estimate the probability of a reviewer citing a manuscript based on reviewing status and our moderating variables. Our baseline model for testing Hypothesis 1 takes the form:

$$P(Learning_i = 1) = (\beta_0 + \beta_1 \times Reviewed_i + \beta_2 \times TeamSize_i + \beta_3 \times SubmissionYear_i + Reviewer\ Productivity\ Measures + Fixed\ Effects + \varepsilon_i)$$

Where Learning_i is the binary learning indicator for reviewer i, Reviewed_i indicates whether reviewer i completed the review, and the remaining terms represent control variables and fixed effects. The coefficient β_1 measures the effect of reviewing on learning, with a positive and significant value supporting Hypothesis 1.

To test Hypothesis 2 on the moderating role of geographic proximity, we extend the model to include an interaction term:

$$P(Learning_i = 1) = (\alpha_0 + \alpha_1 \times Reviewed_i + \alpha_2 \times SameCountry_i + \alpha_3 \times (Reviewed_i \times SameCountry_i) + \alpha_4 \times TeamSize_i + \alpha_5 \times SubmissionYear_i + Reviewer\ Productivity\ Measures + Fixed\ Effects + \varepsilon_i)$$

The coefficient α_3 captures how geographic proximity moderates the effect of reviewing on learning. A negative and significant α_3 would support Hypothesis 2, indicating that geographic distance negatively moderates the learning-by-reviewing effect.

Similarly, for Hypothesis 3 on the moderating role of intellectual distance, we estimate:

$$P(Learning_i = 1) = (\gamma_0 + \gamma_1 \times Reviewed_i + \gamma_2 \times IntellProximity_i + \gamma_3 \times (Reviewed_i \times IntellProximity_i) + \gamma_4 \times TeamSize_i + \gamma_5 \times SubmissionYear_i + Reviewer\ Productivity\ Measures + Fixed\ Effects + \varepsilon_i)$$

The coefficient γ_3 captures how intellectual proximity moderates the effect of reviewing on learning. A positive and significant γ_3 would support Hypothesis 3, indicating that reviewers with high intellectual similarity to the manuscript experience stronger knowledge gains.

To address potential concerns about selection bias and endogeneity, we conduct several robustness checks, including alternative specifications of our dependent variable (different citation windows, citation count instead of binary), different sample restrictions (e.g., including reviewers who auto-declined) and additional control variables and fixed effects. These specifications allow us to test our hypotheses while accounting for potential confounding factors, providing a more comprehensive assessment of the learning-by-reviewing relationship and its contingencies.[4]

4. Results

[4] See Tables A1 to A6 in Appendix A for the detailed results

4.1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Full Sample					
Reviewer Learned (3yr)	104,306	0.023	0.150	0	1
Submission Year	104,306	2018.561	0.496	2018	2019
Final Decision	104,306	0.565	0.496	0	1
Citations (decile)	104,306	2.015	1.383	0	4
Works (decile)	104,306	2.016	1.383	0	4
h-index (decile)	104,306	1.978	1.379	0	4
i10-index (decile)	104,306	2.011	1.380	0	4
Team Size (decile)	104,306	1.796	1.332	0	4
Same Country	104,306	0.112	0.315	0	1
Max Abstract Similarity	96,975	0.522	0.171	-0.165	0.943
Did Not Review Paper (Unavailable for review)					
Reviewer Learned (3yr)	44,896	0.013	0.114	0	1
Submission Year	44,896	2018.562	0.496	2018	2019
Final Decision	44,896	0.631	0.483	0	1
Citations (decile)	44,896	2.195	1.375	0	4
Works (decile)	44,896	2.137	1.368	0	4
h-index (decile)	44,896	2.137	1.378	0	4
i10-index (decile)	44,896	2.148	1.367	0	4
Team Size (decile)	44,896	1.805	1.334	0	4
Same Country	44,896	0.080	0.271	0	1
Max Abstract Similarity	41,725	0.522	0.168	-0.158	0.943
Reviewed Paper (Submitted review)					
Reviewer Learned (3yr)	59,410	0.031	0.173	0	1
Submission Year	59,410	2018.560	0.496	2018	2019
Final Decision	59,410	0.515	0.500	0	1
Citations (decile)	59,410	1.878	1.374	0	4
Works (decile)	59,410	1.924	1.387	0	4
h-index (decile)	59,410	1.859	1.368	0	4
i10-index (decile)	59,410	1.907	1.380	0	4
Team Size (decile)	59,410	1.790	1.330	0	4
Same Country	59,410	0.136	0.343	0	1
Max Abstract Similarity	55,250	0.523	0.173	-0.165	0.927

Table 1: Descriptive statistics of key variables in the analytic sample

Our analytic sample consists of 104,306 reviewer-manuscript pairs across 55 journals in the physical sciences. Before presenting our regression analyses, we examine the patterns of learning-by-reviewing in our data through descriptive statistics.

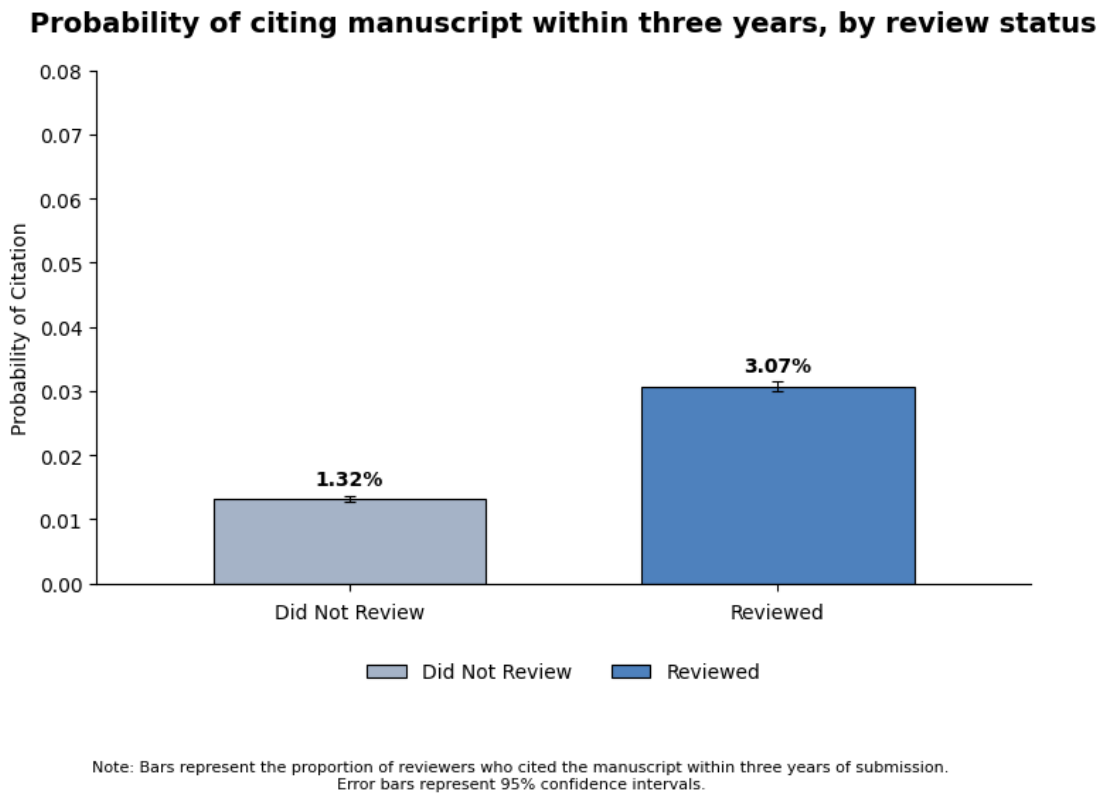


Figure 2: Citation probability by reviewing status

Figure 2 shows the proportion of reviewers who cite the manuscripts they were invited to review within three years, comparing those who completed reviews (treatment group) with those who declined due to unavailability (control group). The raw difference suggests that reviewers who evaluate manuscripts are more likely to subsequently cite them compared to qualified reviewers who were invited but unavailable.

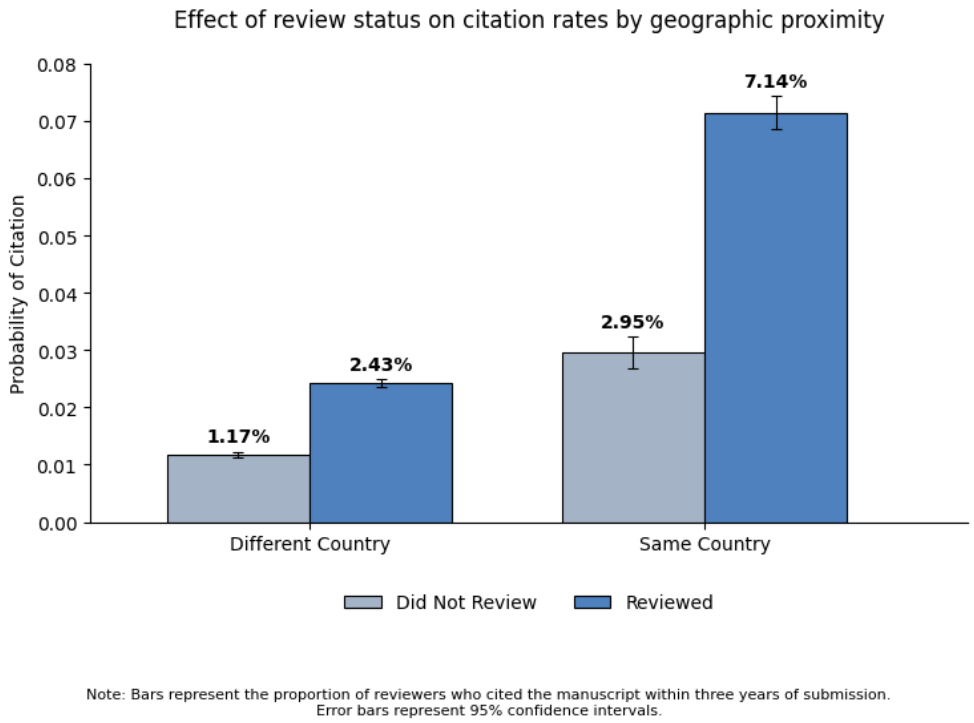


Figure 3a: Citation probability by reviewing status and country difference

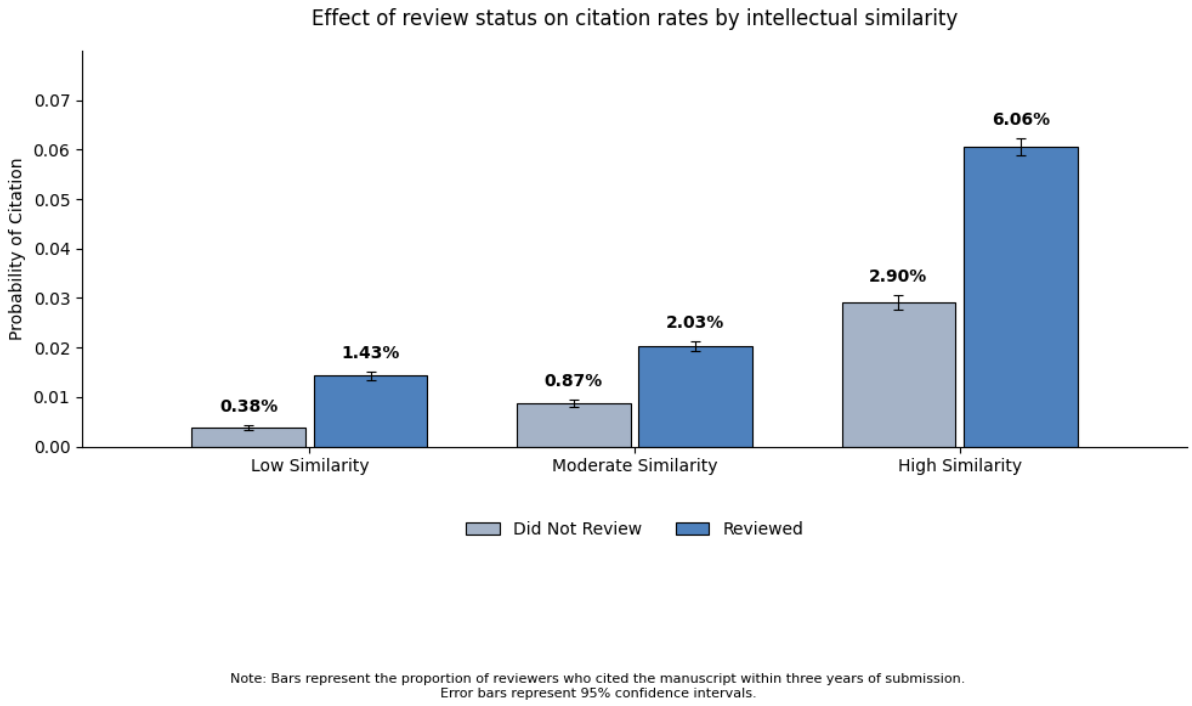


Figure 3b: Citation probability by reviewing status and intellectual distance tier

Figure 3a and 3b further breaks down citation rates by our key moderating variables: geographic proximity and intellectual distance. These descriptive patterns provide initial evidence for our hypothesized relationships, though multivariate analyses are necessary to account for potential confounding factors.

4.2 Main Results

4.2.1 Effect of Reviewing on Knowledge Acquisition

Variable	Model 1	Model 2	Model 3	Model 4
Reviewed	0.018***	0.018***	0.020***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.013***	0.011***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Journal FE			Yes	
Manuscript FE				Yes
Observations	104,306	104,306	104,306	104,306
Pseudo R^2	0.003	0.004	0.004	0.003

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

Table 2: OLS regression results for Hypothesis 1

Table 2 presents the results of our OLS regression models testing Hypothesis 1, which predicted that reviewers acquire knowledge through manuscript evaluation. Model 1 includes only reviewer characteristics and journal fixed effects, while Model 2 adds manuscript-level controls. Across both specifications, we find that completing a review significantly increases the likelihood of citing the manuscript in subsequent work. The coefficient on our Reviewed variable is positive and statistically significant ($p < 0.001$), indicating that, all else equal, reviewers who evaluate a manuscript are more likely to incorporate its knowledge compared to those who were invited but unavailable. This effect remains robust when controlling for reviewer productivity, manuscript characteristics, and journal fixed effects. In terms of magnitude, the average marginal effect indicates that reviewing a manuscript increases the

probability of subsequent citation by approximately 1.8 percentage points, representing more than a twofold increase relative to the baseline citation rate among non-reviewers. This substantial effect supports Hypothesis 1 and suggests that the peer review process serves as an important channel for knowledge acquisition.

4.2.2 Moderating Effect of Geographic Distance

Variable	Model 1	Model 2	Model 3	Model 4
Reviewed	0.013***	0.013***	0.014***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Same Country	0.018***	0.018***	0.014***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
Reviewed × Same Country	0.029***	0.029***	0.033***	0.034***
	(0.003)	(0.003)	(0.003)	(0.004)
Constant	0.012***	0.011***	0.010***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Controls		Yes	Yes	Yes
Journal FE			Yes	
Manuscript FE				Yes
Observations	104,306	104,306	104,306	104,306
Pseudo R^2	0.010	0.011	0.011	0.010

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

Table 3: OLS regression results for Hypothesis 2

Table 3 presents models testing Hypothesis 2, which predicted that geographic distance negatively moderates the learning-by-reviewing effect. The models include the interaction term between *Reviewed* and *Same Country*, which captures how the effect of reviewing differs based on geographic proximity between reviewer and authors. The coefficient on the interaction term with same country is positive and statistically significant across specifications, indicating that the learning benefit of reviewing is larger for reviewers from the same country as the manuscript authors compared to reviewers from different countries. However, considering the non-interaction coefficient terms, we find that the effect of reviewing for reviewers from different countries (1.3%) is similar in size and non-statistically different

from the effect of sharing the same country with the author of the reviewed paper but not reviewing (1.8%). This finding supports Hypothesis 2 and suggests that reviewing partially compensates for the barriers to knowledge flow imposed by geographic distance.

4.2.3 Moderating Effect of Intellectual Distance

Variable	Model 1	Model 2	Model 3	Model 4
Reviewed	-0.009***	-0.009***	-0.009***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.004)
Intellectual Similarity	0.062***	0.062***	0.046***	0.039***
	(0.004)	(0.004)	(0.004)	(0.006)
Reviewed × Intellectual Similarity	0.052***	0.052***	0.056***	0.057***
	(0.006)	(0.006)	(0.006)	(0.007)
Constant	-0.019***	-0.021***	-0.013***	-0.007**
	(0.002)	(0.003)	(0.003)	(0.003)
Controls		Yes	Yes	Yes
Journal FE			Yes	
Manuscript FE				Yes
Observations	96,975	96,975	96,975	96,975
Pseudo R^2	0.015	0.015	0.013	0.015

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

Table 4: OLS regression results for Hypothesis 3

Table 4 presents models testing Hypothesis 3, which predicted that intellectual proximity positively moderates the learning-by-reviewing effect. These models include the interaction between *Reviewed* and *Intellectual Proximity*, our measure of cognitive overlap between reviewer expertise and manuscript content. The coefficient on this interaction term is positive and statistically significant, indicating that reviewers with higher intellectual similarity to the manuscript content experience stronger knowledge gains from reviewing. This result supports Hypothesis 3 and suggests that while reviewing generally facilitates learning, the effect is amplified when reviewers possess relevant domain knowledge that enables them to effectively assimilate new information.

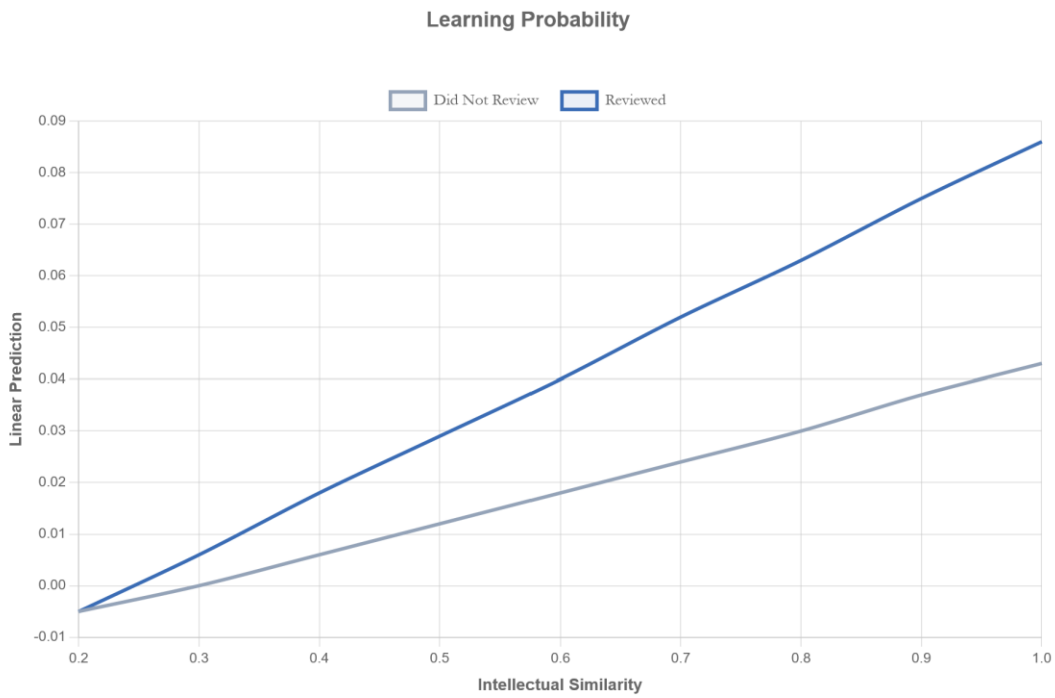


Figure 4: Marginal effects of reviewing on citation probability by intellectual proximity

Figure 4 visualizes how the effect of reviewing varies across different levels of intellectual proximity. The steeper slope at higher levels of intellectual proximity demonstrates that reviewers with greater cognitive overlap with the manuscript content derive greater learning benefits from the review process.

4.3 Robustness Checks

To ensure the validity of our findings, we conducted several robustness checks. First, we tested alternative time windows for measuring citations (2-year and unlimited windows) and found consistent results (see Tables A1 and A4 in Appendix A). Second, we ran logistic specification instead of OLS and our main findings remained robust (see Table A2 in Appendix A). Third, we used a count variable for the number of times the paper reviewed is cited rather than the binary variable, again finding support for our hypotheses (see Table A3 and A5 in Appendix A). Finally we expanded our sample to include

reviewers who declined for reasons other than unavailability with robust findings (see Table A6 in Appendix A).

5. Discussion

This study advances our understanding of expert evaluation by highlighting its role not only as a resource allocation mechanism but also as a significant channel for knowledge transfer. Our results demonstrate that reviewers acquire knowledge through the evaluation process, as evidenced by their increased likelihood of citing reviewed manuscripts in subsequent work. Moreover, we find that both geographic and intellectual distance moderate this learning effect in important ways.

Our findings contribute to several streams of literature at the intersection of knowledge management, scientific collaboration, and peer review processes. First, we extend research on knowledge transfer mechanisms by identifying peer review as a structured process that facilitates deep engagement with new ideas. While existing work has focused on channels such as conferences, collaborations, and mobility (Lane et al., 2020; Catalini, 2018), the peer review process represents a unique and widespread mechanism that has received limited attention as a knowledge transfer channel. Second, our findings on the moderating role of geographic distance contribute to the literature on spatial constraints in knowledge flows. Previous research has documented how geographic proximity facilitates knowledge transfer through increased interaction opportunities and shared contextual understanding (Breschi & Lissoni, 2009; Catalini, Fons-Rosen, & Gaulé, 2020). Our results suggest that formal review processes can partially compensate for these geographic barriers, providing a structured channel for knowledge to flow across distant locations. Interestingly, we find that while unavailable evaluators from the same country as a paper's corresponding author have significantly higher baseline citation rates, evaluators from different countries who reviewed the paper achieved similarly high citation levels. This indicates that structured evaluation of external ideas can compensate for geographic boundaries in knowledge transfer. The effect also appears larger for proximate reviewers, likely because "same-country" does not necessarily mean close proximity but does confer advantages like shared time zones, language, culture, and conference participation opportunities. This insight is particularly relevant as science becomes

increasingly global, with researchers collaborating across institutional and national boundaries. Third, our results on intellectual proximity contribute to debates about optimal cognitive distance in knowledge exchange. While some scholars emphasize the benefits of diverse knowledge bases for innovation (Jeppesen & Lakhani, 2010; Fleming, 2001), others highlight the importance of shared understanding for effective knowledge transfer (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998). Our finding that intellectual proximity enhances learning-by-evaluating suggests that in the context of peer review—where manuscripts contain inherently novel elements—the ability to comprehend and assimilate new information may outweigh the potential benefits of extreme cognitive distance.

Beyond these theoretical contributions, our findings connect to several influential streams of research. First, they build on absorptive capacity theory, which emphasizes the role of prior knowledge in assimilating new information (Cohen and Levinthal, 1990). Second, they relate to knowledge recombination perspectives, which highlight how innovation emerges from connecting previously separate ideas (Fleming, 2001; Uzzi, Mukherjee, Stringer, and Jones, 2013). Third, they engage with studies on distance-related barriers to knowledge sharing (Breschi and Lissoni, 2009; Catalini et al., 2020). Additionally, our work contributes to research on public goods provision and organizational learning. The literature on public goods has emphasized both altruistic and social motives for contribution, as seen in studies of Wikipedia (Zhang and Zhu, 2011; Ayoubi & Thurm, 2023), as well as private benefits like signalling in open-source software development (Lerner and Tirole, 2002). However, these findings have remained disconnected from evaluation contexts. By identifying knowledge spillovers in evaluation processes, we provide a novel perspective on why individuals participate in seemingly under-incentivized activities (Engers and Gans, 1998).

These knowledge spillovers emerge as the peer review process operates as both a quality control mechanism and a potential learning opportunity for evaluators. Beyond its gatekeeping role in ensuring methodological rigor (Tomkins, Zhang, and Heavlin, 2017; Bol, de Vaan, and van de Rijt, 2018), peer review serves as a conduit for knowledge acquisition. Reviewers engaging with cutting-edge research encounter novel ideas, methods, and perspectives that could stimulate their intellectual development

and spark knowledge spillovers (Catalini et al., 2020; Cohen and Levinthal, 1990). This knowledge transfer potential aligns with organizational learning principles: just as firms learn through external interactions (Cohen and Levinthal, 1990; Argote, 2012; Hwang, Singh & Argote, 2015), reviewers can benefit from engaging with manuscripts spanning diverse fields, regions, and communities. The structured nature of peer review, requiring close attention to content, methods, and arguments, creates conditions conducive to deep learning (Bryan, Karlan, and Nelson, 2010)—potentially fostering creativity and new research directions through knowledge recombination (Fleming, 2001; Uzzi et al., 2013).

Our findings have important practical implications well beyond addressing "reviewer fatigue"—a growing concern in scientific publishing (Kovanis et al., 2016; Vesper, 2018). While editorial teams increasingly struggle to recruit and motivate qualified reviewers as demands on researchers' time intensify (Fox et al., 2017; Yu et al, 2024), our findings have broader relevance. Many organizations across diverse contexts conduct project evaluations using internal or external experts, making it crucial to understand the full set of costs and benefits associated with these evaluation systems. The learning benefits we document offer a compelling alternative narrative about the value of evaluation from the evaluator's perspective. Instead of viewing evaluation solely as a professional service obligation driven by altruism or reputation concerns, organizations and individuals might recognize it as an opportunity for knowledge acquisition and professional development. Journal editors and publishers could leverage these insights in several ways. First, they might explicitly communicate the potential learning benefits when inviting reviewers, possibly increasing acceptance rates. Second, our findings on moderating factors suggest possibilities for strategic reviewer assignment: editors could consider geographic and intellectual proximity when matching reviewers to manuscripts, potentially optimizing both evaluation quality and knowledge dissemination. Third, implementing reviewer training programs that emphasize effective knowledge extraction techniques could enhance both review quality and learning outcomes.

From a policy perspective, our findings suggest that evaluation systems serve dual purposes in scientific advancement. Beyond their gatekeeping function, they represent an important mechanism for

knowledge dissemination across geographic and disciplinary boundaries. This insight is particularly important given recent trends toward delegating evaluations to artificial intelligence systems (Lane et al., 2024; Doshi et al., 2024). While AI-based solutions offer promising efficiency gains, the rush toward automation may overlook the critical role of peer review as a knowledge transfer channel with valuable spillover benefits for human reviewers. Funding agencies and institutions might consider more explicit recognition of reviewing activities in evaluation metrics, acknowledging their contribution not only to quality assurance but also to knowledge flow within scientific communities (Yu et al., 2024). At the organizational level, our findings highlight peer review's potential as a mechanism for breaking down silos and facilitating knowledge sharing across boundaries. The structured nature of evaluation creates formal pathways for knowledge to flow between researchers who might otherwise remain isolated within specialized domains or geographic locations (Argote & Ingram, 2000; Singh, 2005). Organizations can leverage this dual function of evaluation—quality control and knowledge integration—by strategically assigning evaluators to create productive bridges across departments, disciplines, and regions.

Despite these contributions, our study has several limitations that suggest directions for future research. First, our identification strategy relies on comparing reviewers who completed evaluations with those who declined due to unavailability, a plausibly exogenous reason for non-participation. However, systematic differences between these reviewer groups may still exist if more engaged or curious researchers are more likely to make time for papers they find interesting or relevant to their work. To address this concern, we conduct several robustness checks. We test alternative control groups including reviewers who auto-declined (who had no opportunity to assess paper content before declining) and find consistent results. We also examine whether our findings differ for anonymized versus non-anonymized manuscripts to rule out strategic citation behavior, and test specifications that include reviewers who declined for other reasons beyond unavailability and find consistent robust overall. Additionally, our focus on post-publication peer review of completed research may limit generalizability to other evaluation contexts. The dynamics of learning-by-reviewing may differ substantially in prospective evaluation settings, such as grant proposal review, where evaluators assess early-stage ideas

with greater uncertainty and different cognitive demands. The knowledge acquisition patterns we observe for relatively mature scientific contributions may not extend to the evaluation of preliminary or speculative research proposals. Third, our measurement approach also has limitations. Citation behavior, while observable, may not capture all forms of knowledge acquisition that occur during peer review or inflate some non-learning behavior (Catalini et al., 2015). Reviewers may absorb methodological insights, theoretical frameworks, or domain knowledge that influences their thinking without resulting in direct citations. The intellectual distance measure, based on semantic similarity between abstracts, represents only one dimension of cognitive proximity and may not fully capture the complexity of knowledge relationships across research domains.

Future work could address these limitations through several avenues. Experimental approaches, such as randomized reviewer assignments or field experiments with journal editors, could provide stronger causal identification of learning effects. Studies that include unpublished manuscripts or track submission histories across multiple venues would help address selection bias concerns. Additionally, research examining learning-by-reviewing in prospective evaluation settings, such as grant panels or early-stage innovation contests, would illuminate whether our findings generalize beyond post-publication peer review. Finally, complementing citation analysis with survey data, interviews, or text analysis of reviewers' subsequent work could provide richer evidence of knowledge acquisition mechanisms and help validate our core theoretical arguments about learning through evaluation.

6. Conclusion

Building on our theoretical contributions, this study provides compelling evidence that peer review serves as a significant knowledge acquisition channel—an insight with direct implications for addressing growing concerns about reviewer recruitment and retention in scientific publishing. Rather than viewing evaluation solely as an under-incentivized service, it can be recognized as a valuable opportunity for professional development and knowledge acquisition, with reviewers more than twice as likely to integrate evaluated knowledge into their own work. For policy makers, our findings support the explicit recognition of reviewing activities in academic evaluation metrics. The knowledge spillovers we

document demonstrate that evaluation systems simultaneously serve resource allocation and knowledge dissemination functions, providing empirical justification for policies that incentivize participation in peer review. The moderating effects of geographic and intellectual proximity further suggest opportunities for strategic reviewer assignment to optimize both evaluation quality and knowledge flow.

Beyond addressing "reviewer fatigue," these insights extend to organizational settings broadly, offering a novel perspective on why individuals participate in seemingly under-incentivized activities. As scientific and business organizations increasingly explore automated alternatives to human evaluation, our study highlights important but often overlooked benefits of traditional expert review systems. Future research should examine how these learning dynamics manifest across disciplines and institutional contexts, and how evaluation systems might be intentionally designed to enhance knowledge spillovers without compromising assessment integrity. By documenting the multifaceted value of peer review, this study contributes to ongoing efforts to sustain effective evaluation systems amid mounting demands on experts' time and attention.

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Appendix

A. Robustness Check Tables

Table A1: Regression Results (2-Year Learning)

Variable	Model 1	Model 2	Model 3	Model 4
Reviewed	0.013***	0.013***	0.015***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.009***	0.008***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Journal FE			Yes	
Manuscript FE				Yes
Observations	104,306	104,306	104,306	104,306
Pseudo R^2	0.003	0.003	0.003	0.003

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

Table A2: Logistic Regression Results

Variable	Model 1	Model 2
Reviewed	0.865***	0.867***
	(0.048)	(0.048)
Team Size		0.078***
		(0.015)
Year 2019		-0.093*
		(0.041)
Constant	-4.317***	-4.412***
	(0.041)	(0.056)
Controls	No	Yes
Observations	104,306	104,306
Pseudo R^2	0.016	0.018

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

Table A3: Regression Results (Continuous Measure of Learning)

Variable	Model 1	Model 2	Model 3	Model 4
Reviewed	0.036***	0.036***	0.039***	0.037***
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.017***	0.019***	0.019***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls	No	Yes	Yes	Yes
Journal FE			Yes	
Manuscript FE				Yes
Observations	104,306	104,306	104,306	104,306
R^2	0.003	0.003	0.004	0.003

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

Table A4: Regression Results with Country Interaction (2-Year Learning)

Variable	Model 1	Model 2	Model 3	Model 4
Reviewed	0.010***	0.010***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Same Country	0.012***	0.012***	0.009***	0.011***
	(0.002)	(0.002)	(0.002)	(0.003)
Reviewed ×	0.021***	0.021***	0.024***	0.022***
Same Country	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.008***	0.008***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	No	Yes	Yes	Yes
Journal FE			Yes	
Manuscript FE				Yes
Observations	104,306	104,306	104,306	104,306
R^2	0.007	0.008	0.008	0.007

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

Table A5: Regression Results with Country Interaction (Continuous Measure)

Variable	Model 1	Model 2	Model 3	Model 4
Reviewed	0.022***	0.022***	0.025***	0.023***
	(0.002)	(0.002)	(0.002)	(0.003)
Same Country	0.024***	0.024***	0.018***	0.026***
	(0.006)	(0.006)	(0.006)	(0.007)
Reviewed ×	0.089***	0.089***	0.095***	0.093***
Same Country	(0.007)	(0.007)	(0.007)	(0.008)
Constant	0.015***	0.019***	0.019***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls	No	Yes	Yes	Yes
Journal FE			Yes	
Manuscript FE				Yes
Observations	104,306	104,306	104,306	104,306
R^2	0.011	0.012	0.012	0.011

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

Table A6: Regression Results (Auto-Decline as Control Sample)

Variable	Model 1	Model 2	Model 3	Model 4
Reviewed	0.021***	0.021***	0.017***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.010***	0.008***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	No	Yes	Yes	Yes
Journal FE			Yes	
Manuscript FE				Yes
Observations	103,193	103,193	103,193	103,193
R^2	0.005	0.005	0.003	0.004

*Note: Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10*

B. Additional Results

Figure B1

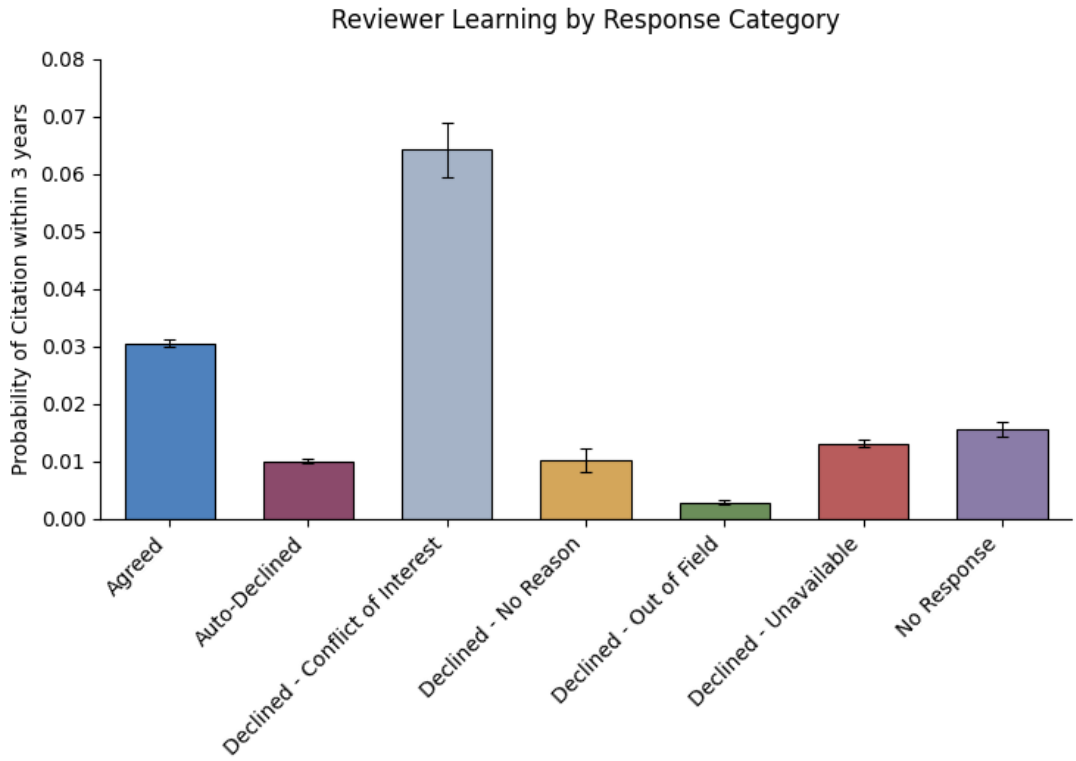


Figure B2

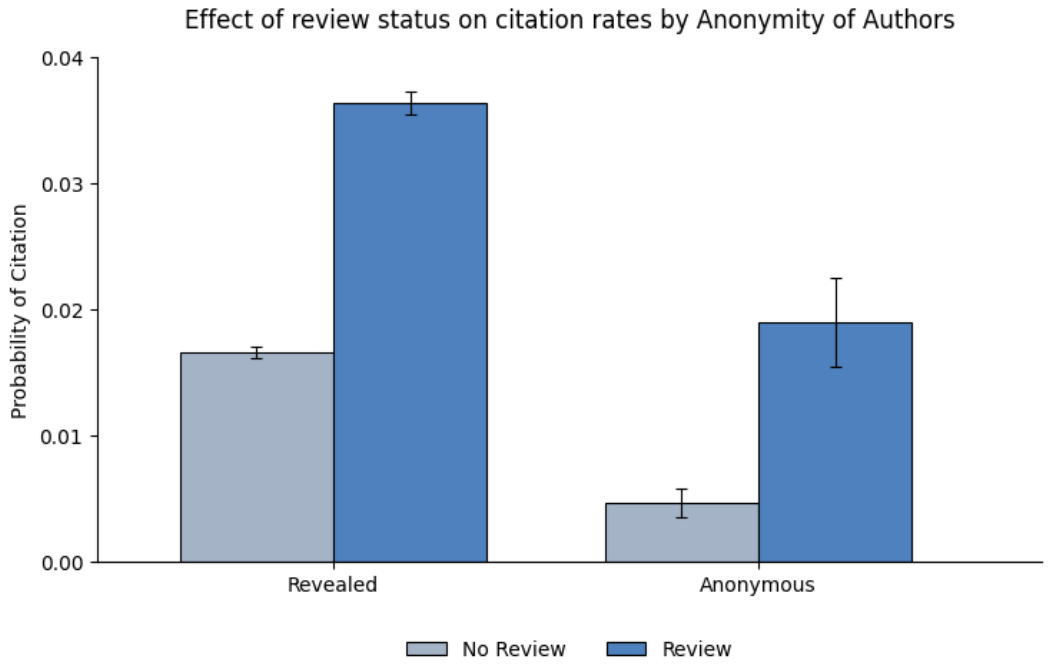


Figure B3

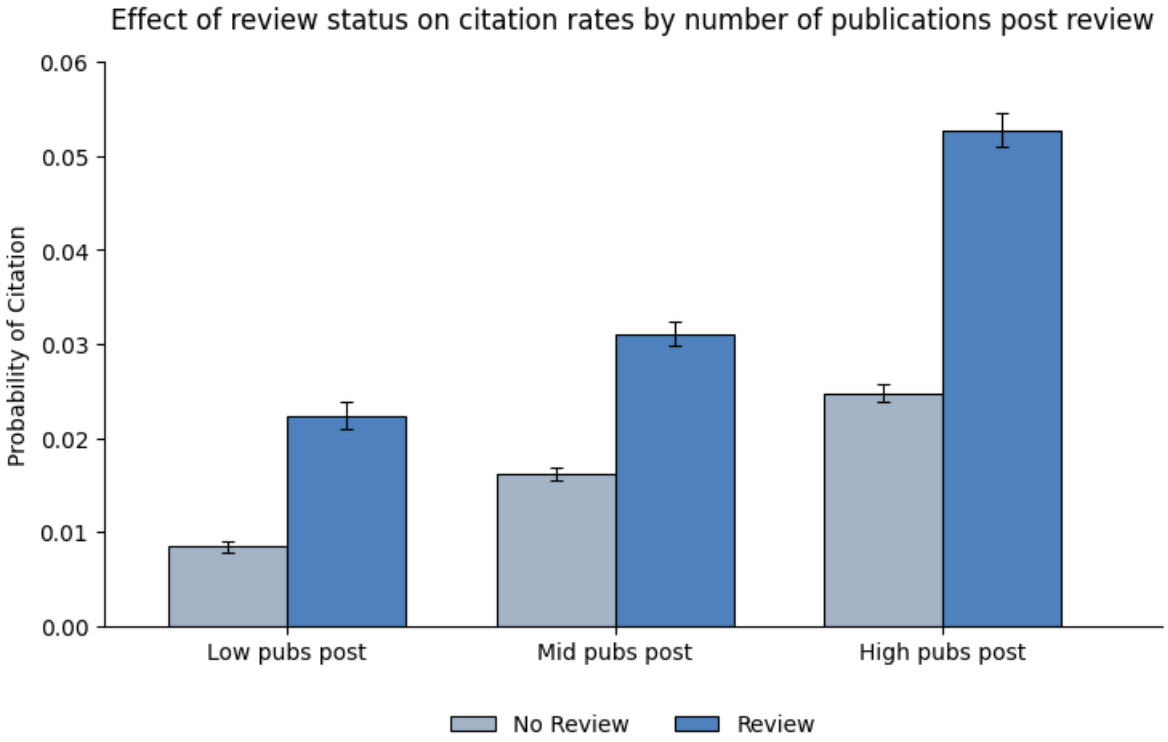


Figure B4

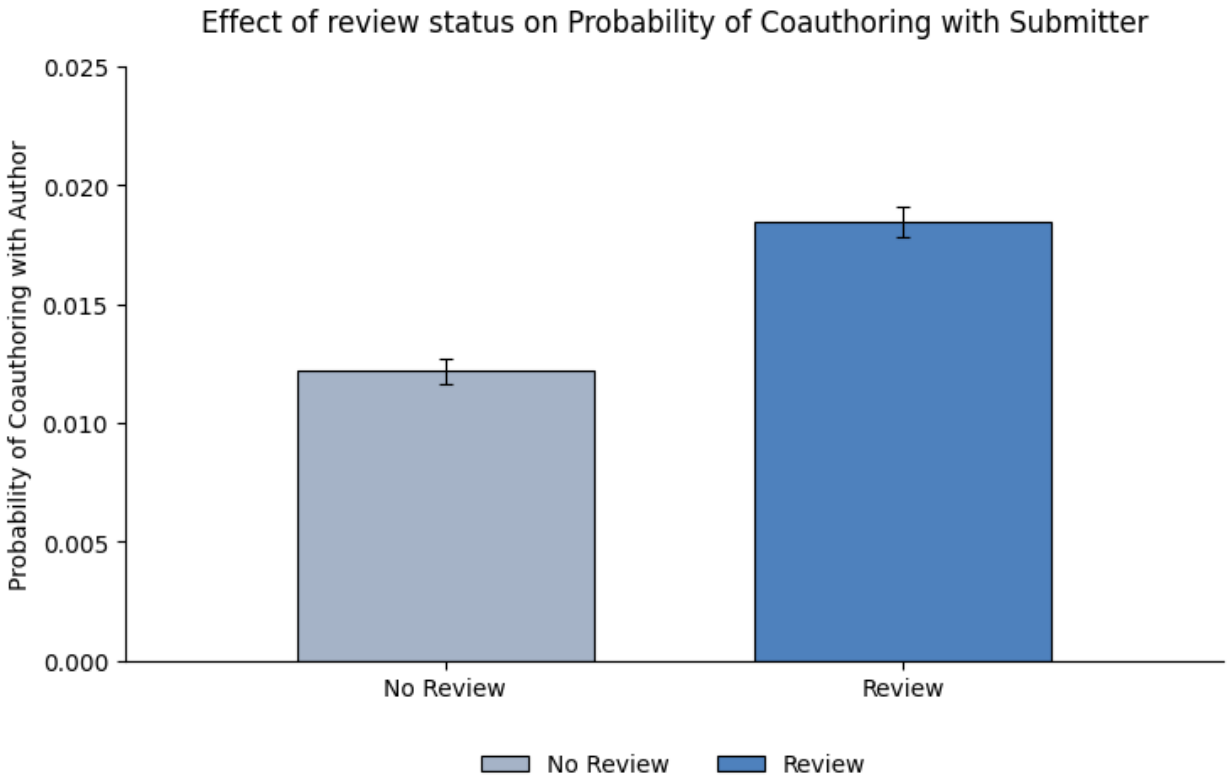
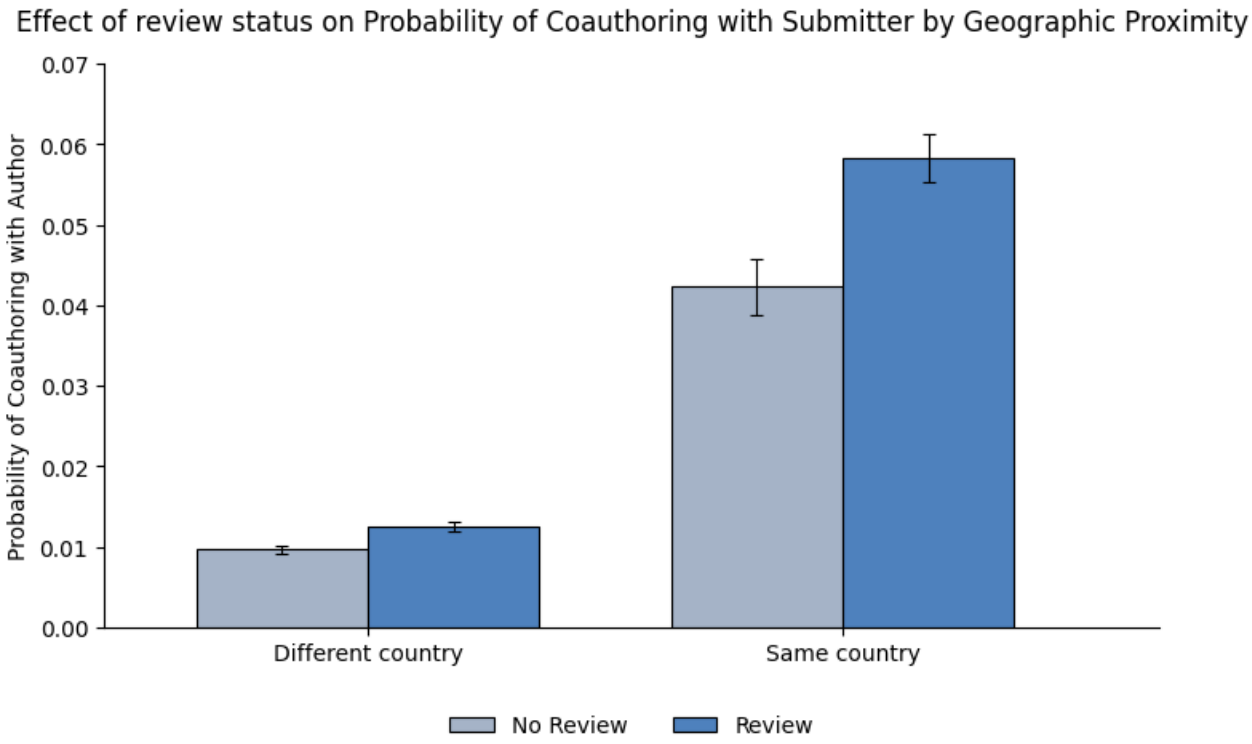


Figure B5


Effect of review status on Probability of Coauthoring with Submitter by Geographic Proximity
Probability of Coauthoring with Author
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Different country
Same country
No Review
Review