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Open access and the flow of knowledge into technology: Evidence from journal transitions to full and immediate OA

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Abstract

Scientific knowledge forms the foundation of technological innovation, yet how to effectively facilitate its translation into applied technologies remains underexplored. Existing research has largely focused on measuring the linkage between science and technology, while overlooking the institutional mechanisms that can actively promote this process. Open Access (OA), by improving the accessibility and visibility of scientific outputs, presents a promising pathway to accelerate knowledge diffusion. This study investigates whether and how journal transitions to OA foster the uptake of scientific knowledge in technological domains, using agriculture as a representative field. We compile a panel dataset of 299 agricultural journals (1990–2024) and employ a multiperiod Difference-in-Differences (DID) framework. The results show that journal transitions to full and immediate OA significantly increase the number of patent citations per article. Mechanism analysis further reveals that OA enhances social media attention and early scholarly usage, thereby facilitating the translation of research into patents. These findings highlight OA as not merely a tool for improving scholarly access, but also a strategic driver for research translation into technological innovation.

1 | INTRODUCTION

Amid the escalating global competition driven by knowledge-based economies, the value of scientific output is increasingly determined by its ability to be effectively translated into socially usable technological outcomes. As the foundational input of innovation systems, scientific knowledge must be efficiently transformed into technological applications—a process that not only affects the allocation efficiency of research resources, but also plays a decisive role in promoting industrial upgrading and enhancing national innovation capacity (Balconi et al., 2010; Bush, 1945; Stokes, 1997). Accordingly, how to facilitate the smooth "flow" of scientific knowledge into the technological system has become a central concern in science policy, innovation governance, and scientometric research (Jaffe & Trajtenberg, 2002; Narin et al., 1997).

Although extensive research has examined the flow of scientific knowledge into technological systems, most studies have primarily focused on mapping the pathways and structures through which knowledge flows. Griliches (1998) tracked the movement of knowledge from science to technology using citations in patents, proposing that the intensity of patent-to-paper citations can serve as a proxy for measuring the strength of science–technology linkages (Ahmadpoor & Jones, 2017; Jaffe et al., 1993). Narin et al. (1997) systematically analyzed US patent citations to scientific literature from 1979 to 1994, revealing that the degree of science–technology convergence was highest in the life sciences. Building on this, Michel and Bettels (2001) examined patent citation networks to further uncover the structural patterns of knowledge flow. Recent studies have also advanced various metrics for quantifying the linkages between science and technology

(Meng et al., 2024; Xu et al., 2019; Xu et al., 2022). However, while these studies depict the *status quo* of science-to-technology knowledge transfer, they offer limited insights into *how* such translational processes can be actively facilitated.

In practice, fostering effective linkages between science and technology typically involves three critical stages. First, increasing the quantity and quality of basic research serves as the foundational supply for technological innovation (Balland & Boschma, 2022). Second, broadening the dissemination channels of scientific output ensures that knowledge can be recognized and understood across organizational and institutional boundaries (Tennant et al., 2016). Third, enhancing the absorptive and recombinative capacity of technological systems is essential for translating scientific insights into usable technologies (Arora et al., 2015; Cohen & Levinthal, 1990). However, both in the institutional design of science policy and in the prevailing paradigms of scientometric and innovation research, the first stage has long been the primary focus. A substantial body of literature emphasizes "supply-side" reforms—such as increasing research output, optimizing academic evaluation criteria, and incentivizing interdisciplinary collaboration (Newman, 2001; Weinberg et al., 2014). In contrast, studies addressing how scientific knowledge is efficiently transformed into technological resources, how the science-to-application pipeline can be shortened, and how institutionalized and sustainable mechanisms of knowledge translation can be built remain relatively underexplored (Balconi et al., 2010).

Existing research has clearly demonstrated that the movement of knowledge from generation to application is not spontaneous, but instead requires systemic coordination across institutional structures, dissemination mechanisms, and user accessibility (Bozeman, 2000). The institutional environment plays a decisive role in shaping both the feasibility and trajectory of knowledge translation. For instance, variations in innovation policy directly affect the capacity of patents to absorb scientific knowledge (Ostrom, 2010). In developing countries, the flow of knowledge often follows an "outward-oriented" trajectory, relying heavily on external scientific resources for local technological development (Wang et al., 2015).

As a major institutional shift in 21st-century scientific communication, Open Access (OA) offers a foundational mechanism for facilitating the flow of scientific knowledge into technological systems. By eliminating financial barriers to access and enhancing the visibility and reusability of research outputs, OA enables knowledge to circulate beyond high-resource institutions and reach broader segments of society (Li et al., 2021; Schiltz, 2018; Suber, 2012). In doing so, it holds the potential to expand the pathways through which science disseminates toward technology, thereby fostering more efficient knowledge translation (Solomon & Björk, 2012). However, despite its rapid rise, the role of open access within the broader chain of knowledge transformation remains insufficiently explored.

Empirical studies on OA have primarily focused on its impact on academic visibility, particularly whether OA increases citation rates (Ming & Zhao, 2022; Piwowar et al., 2018; Tennant et al., 2016; Zhang et al., 2021). Some research has further explored how OA facilitates the diffusion of science to the public via social media platforms (Teplitskiy et al., 2017), while others have examined the relationship between article processing charges (APCs) and scholarly impact (Pinfield et al., 2017). Meanwhile, concerns have also been raised about potential declines in publication quality associated with OA business models (Van Vlokhoven, 2019). Therefore, although OA may enhance the visibility of research outputs, the underlying mechanisms through which it facilitates the transformation of scientific knowledge into usable technological resources remain under-investigated (Roach & Cohen, 2013).

This study starts from an underexplored perspective: OA is not only a channel for knowledge dissemination but also a potential policy tool for reshaping science-to-technology translation. OA lowers entry barriers by altering access and dissemination structures. We propose two mechanism pathways through which OA enhances knowledge diffusion: increased social media visibility and greater academic platform usage—reflecting how OA boosts both public discoverability and scholarly engagement.

Accordingly, this study addresses the following research questions:

1. *At the empirical level*, are OA articles more likely to be cited by patents?
2. *At the causal level*, do OA-related policy reforms causally promote the citation of scientific articles by patents?
3. *At the mechanism level*, do social media attention and academic usage function as pathways through which OA facilitates the translation of scientific knowledge into technology?

While a few recent studies have observed that OA articles are more likely to be cited by patents (Probst et al., 2023), the existing literature remains largely descriptive and cross-sectional in nature, offering limited insights into whether and how OA facilitates the translation of scientific knowledge into technology. Most prior work lacks robust causal identification strategies and systematic analysis of potential mechanisms (Craig et al., 2007). To address this gap, we exploit a quasi-natural experimental setting based on journal-level OA policy reforms. Specifically, we leverage the structural transition toward OA among SCI-indexed journals in the field of agriculture between 1990 and 2024 to estimate the causal effects of OA exposure on patent citations. We implement a multi-period difference-in-differences (DID) design, complemented by event study models, placebo tests, and pre-trend controls to ensure identification robustness.

From a theoretical perspective, it extends the paradigm of research on science-to-technology knowledge translation in three key ways. First, it shifts the focus from measuring knowledge flows to facilitating them, underscoring the critical role of institutional and dissemination mechanisms. Second, it expands the scope of OA research beyond the academic domain by examining its influence on technological uptake—specifically, patent citations. Third, it identifies two mechanism pathways—social media attention and scholarly usage—through which OA promotes knowledge translation, thereby revealing the multidimensional nature of OA's impact.

From a practical standpoint, the study provides quasi-experimental evidence based on a large-scale panel of journals in the agricultural sciences, addressing a central policy question: Does open access accelerate the flow of science into technology? The findings offer new empirical insights and an analytical framework for understanding and improving the institutional foundations that enable the effective translation of scientific knowledge into technological applications.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 introduces the theoretical framework and develops the research hypotheses. Section 4 describes the data sources and variable construction, and outlines the empirical strategy and model specification. Section 5 presents the baseline regression results and a series of robustness checks, and investigates the underlying mechanisms through which open access influences knowledge translation. Finally, Section 6 concludes the study by summarizing the key findings, discussing policy implications, and outlining the limitations and directions for future research.

2 | LITERATURE REVIEW

2.1 | Citation advantage of open access

OA has been widely regarded as a tool to enhance *knowledge accessibility*, defined as the extent to which potential users can access research outputs without financial or institutional barriers. A large body of literature has examined the impact of OA on readership behavior, scholarly usage, and citation performance. Among these, whether OA confers a "*citation advantage*" has remained a central and ongoing debate in scholarly communication (Li et al., 2021; Tennant et al., 2016; Zhang et al., 2021).

Early studies generally found that OA articles tend to receive more citations, possibly due to broader access and faster dissemination (Eysenbach, 2006; Gargouri et al., 2010). However, subsequent work by Craig et al. (2007) and Davis (2011), based on randomized trials, reported a more limited citation effect and raised concerns about self-selection bias—particularly the tendency for higher-quality articles to be made OA by their authors.

To address these concerns, more recent studies have adopted natural experiments or propensity score matching techniques to estimate the causal effects of OA. For instance, Piwowar et al. (2018) analyzed over 620,000 OA articles and found that, on average, OA increased citations by 18% across disciplines, with *Green OA* exhibiting especially strong effects. These findings contribute robust empirical support to the argument that OA improves the accessibility and impact of scientific knowledge.

2.2 | From academic impact to technological impact

The shift from academic to technological impact represents a critical transition in OA research. In recent years, scholars have increasingly extended the OA research agenda to technological systems, exploring how OA facilitates the translation of scientific outputs into patents, firms, and industrial applications. OA has been recognized as a key instrument in supporting open innovation beyond firm boundaries (Chesbrough, 2003).

Empirical evidence has begun to confirm this link. For example, Jahn et al. (2022), using a multidisciplinary sample from Germany, found that OA articles are significantly more likely to be cited by patents—particularly in biotechnology, energy, and other high-tech sectors. Similarly, Dorta-González et al. (2025), in a large-scale analysis of 117,590 papers, showed that OA articles have a systematically higher probability of being cited in patents compared with their non-OA counterparts.

A growing number of studies have also examined disciplinary heterogeneity in this relationship. Maddi (2024) reported that OA articles are cited by patents 73% more often in biology and 27% more often in medicine than non-OA articles, with significant effects also observed in fields such as chemistry and computer science.

Further causal evidence comes from studies exploiting policy reforms as natural experiments. Bryan and Ozcan (2021) employed a regression discontinuity design (RDD) using the NIH OA policy and found that OA significantly increased the likelihood of scientific work being cited in corporate patents, particularly benefiting small and medium-sized enterprises (SMEs). Probst et al. (2023), leveraging the US Department of Energy's mandatory OA mandate, found that OA increased the likelihood of patent citation by an average of 42%, highlighting the structural impact of OA policies on knowledge accessibility and technological uptake.

In addition, Wang et al. (2025) focused on open-access preprints and found that their early and rapid dissemination enhances the discoverability of scientific results in the patent system. These findings underscore the potential of open science to accelerate early-stage knowledge translation into technological domains.

2.3 | Research gap

Although growing evidence links OA to patent citations, several gaps remain. First, most studies use cross-sectional or correlation-based designs, providing limited causal evidence on whether OA accelerates science-to-technology translation, which weakens policy relevance. Second, while research has emphasized OA's role in access and visibility, the mechanisms linking OA to technological uptake—such as social media exposure or early academic usage—are underexplored. Third, prior work often centers on specific disciplines or countries, leaving heterogeneity across fields and applications largely unexamined.

Addressing these gaps requires moving beyond descriptive comparisons toward causal and mechanism-oriented inquiry, systematically assessing how OA reshapes diffusion pathways and the institutional mechanisms mediating knowledge spillovers.

3 | THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

Grounded in theories of knowledge spillover, as well as frameworks on the dissemination and digital visibility of scientific outputs, it is assumed that OA can accelerate the flow of scientific knowledge into technological systems through multiple mechanisms. This section elaborates the theoretical logic underpinning the role of OA in facilitating knowledge translation, and develops a set of testable research hypotheses based on these foundations.

3.1 | Information accessibility mechanism: Open access and knowledge spillover

According to knowledge spillover theory, scientific research outputs—being non-rivalrous and non-excludable—can generate value beyond their original producers, as they are absorbed, recombined, and eventually transformed into technological outputs by other actors in society (Arrow, 1962; Romer, 1990). A key precondition for such spillovers lies in whether potential users possess sufficient capabilities to access, comprehend, and absorb the knowledge in question (Cohen & Levinthal, 1990).

Under traditional access models, scientific knowledge was largely confined to academia, while firms and the public faced barriers to current research. OA removes paywalls and licensing restrictions, increasing accessibility and dissemination speed (Probst et al., 2023). This accelerates the flow of knowledge from discovery to application, enabling absorptive firms to identify and use cutting-edge findings for innovation (Maddi, 2024).

However, OA alone cannot ensure effective use, as comprehension and application still require technical expertise and absorptive capacity. Nonetheless, by providing the foundational step of accessibility, OA substantially increases the likelihood that scientific knowledge will spill over into technological applications.

> **H1.** Open access facilitates the flow of scientific knowledge into technological systems by improving information accessibility.

3.2 | Digital attention mechanism: Open access and social media visibility

With the rise of digital scholarly communication, the impact of scientific outputs is no longer limited to traditional academic citations. Increasingly, "digital attention"—as captured by social media and online platforms—has emerged as a valuable complement for assessing the broader influence of research. According to altmetric framework, tracking digital traces across platforms can provide real-time insights into the public visibility and dissemination trajectory of scholarly outputs (García-Villar, 2021).

Open access enhances the online availability of scientific research and, in doing so, significantly broadens its dissemination reach on social media platforms, thereby increasing both digital visibility and potential technological influence. Empirical studies have shown that OA articles receive substantially more attention on social media and tend to be more highly cited on average than their non-OA counterparts (Vadhera et al., 2022). This so-called "open access advantage" can be attributed to the removal of access barriers, which lowers the threshold for discovery and engagement by researchers, journalists, and the public. As a result, OA articles are more easily read, shared, and discussed.

Moreover, social media exposure enables both active and passive discovery of scientific content by technical users. In line with diffusion of innovation theory, early-stage attention increases the likelihood that knowledge will be adopted and reused in subsequent phases (Eysenbach, 2011). Thus, increased social media visibility may enhance the probability that scientific work is recognized and absorbed by actors engaged in technological development. Platforms such as Twitter have therefore become important channels for disseminating research beyond academia. A considerable share of posts mentioning scholarly papers come from industry and technical professionals, indicating that social media fosters interaction between scientific research and technological practice (Haustein, 2019).

Recent research further supports the idea that social media is actively used by technical and professional communities, thereby extending the audience of scientific knowledge beyond academia. For example, Van Zoonen et al. (2016) show that employees frequently use Twitter to discuss work-related issues, forming a typology of organizational engagement online. Similarly, Zhang et al. (2023) find that workplace social media usage promotes employee creativity by facilitating knowledge sharing and reducing knowledge manipulation. Building on social cognitive theory, Cao et al. (2024) demonstrate that social media capabilities strengthen employees' knowledge reuse and green innovation behavior.

In summary, by granting scientific research greater digital visibility, OA expands its dissemination pathways across social and non-academic platforms. This not only strengthens the public reach of scholarly impact but also creates additional entry points for the translation of science into technology.

> **H2.** Open access indirectly promotes the flow of scientific knowledge into technological systems by increasing attention on platforms such as social media.

3.3 | Scholarly usage mechanism: Open access and engagement on academic platforms

Beyond social media, the dissemination and utilization of scientific knowledge within professional academic communities also play a critical role in shaping its likelihood of being cited and translated into technological applications. In the digital era, reference management and academic networking platforms—such as Mendeley and ResearchGate—have become essential channels through which researchers store, read, and share scholarly literature. Among these, the number of Mendeley Readers has been widely adopted as a proxy indicator of a paper's usage and readership (Maflahi & Thelwall, 2018).

Access and readership are prerequisites for knowledge use. Because OA articles eliminate access barriers, they are more likely to be discovered, downloaded, and read by a broader community of researchers. This is directly reflected in higher Mendeley readership counts. Importantly, the Mendeley user base includes not only academic scholars but also industry practitioners, such as R&D personnel and technical consultants (Mohammadi et al., 2015). Thus, high engagement on such platforms signals not only the scientific relevance of an article, but also increases its visibility to actors involved in technology development and application (Thelwall, 2018).

According to Mohammadi et al. (2015), Mendeley's readership composition includes a measurable proportion of users affiliated with non-academic institutions across disciplines, typically ranging from 3.3% to 5.8%. Furthermore, Fang et al. (2024) explicitly define "researcher" as a user category distinct from faculty, encompassing individuals engaged in research within non-academic organizations. Their analysis indicates that this group generally constitutes 16%–18% of total readers, demonstrating a consistent and meaningful presence of technically oriented users engaging with scholarly publications on these platforms.

This observation aligns with the Pasteur's Quadrant framework (Stokes, 1997), which emphasizes that scientific inquiry and technological application are not mutually exclusive. Many research activities fall into "use-inspired basic research," simultaneously pursuing scientific understanding and technological usefulness. Consequently, both academic scientists and industry R&D personnel often face the need to generate scientific and technological outputs at the same time, making continuous literature reading and knowledge tracking essential inputs for both groups. Platforms such as Twitter and Mendeley lower access barriers and enable users from different organizational backgrounds to engage with frontier research more easily. In addition, information encounter theory suggests that individuals in digital environments often come across knowledge relevant to their professional interests outside deliberate search processes (Erdelez, 1995). This creates an additional—but not exclusive—pathway through which scientific articles

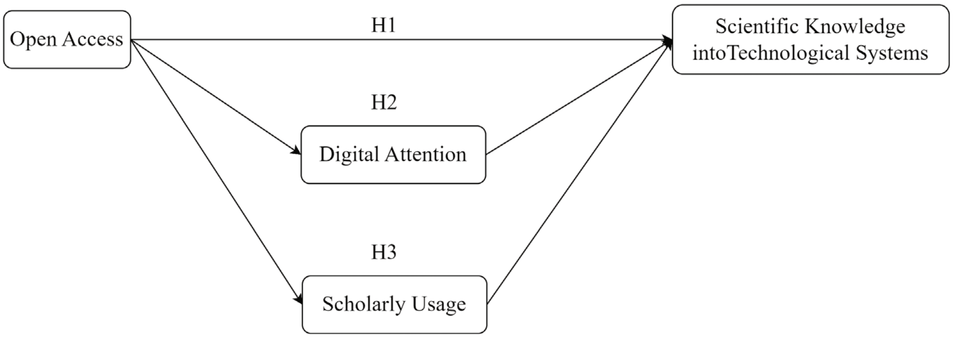

FIGURE 1 Hypothesized pathways from OA to technology.

may diffuse from the academic domain into technological applications. Based on this perspective, we view readership and visibility on such platforms as conditions that may support a *partial* mediating mechanism rather than a dominant or exhaustive one.

In summary, by improving the accessibility and usage of scientific literature on specialized academic platforms, OA strengthens both the scholarly dissemination and the practical influence of research outputs, thereby creating favorable conditions for their integration into technological systems.

> **H3.** Open access indirectly promotes the flow of scientific knowledge into technology by increasing its usage on academic literature platforms.

Figure 1 presents the directed acyclic graph (DAG) of our causal framework. The DAG clarifies the hypothesized pathways through which Open Access (OA) influences the flow of scientific knowledge into technological systems.

4 | DATA AND METHODS

4.1 | Data sources

This study focuses on agricultural sciences, an application-oriented field that relies on advances in areas such as crop improvement and pest management, making it well-suited for analyzing science–technology spillovers. Under subscription models, access barriers have been especially restrictive for public breeding programs and small-to-medium seed enterprises in developing countries. In this context, OA offers a strong marginal effect, providing an ideal setting to examine its institutional role in knowledge dissemination and technological uptake.

We construct a panel dataset for 1980–2024 using the Web of Science (WoS) Core Collection. Based on WoS subject classifications, the study covers seven second-level subfields within "Agricultural Sciences."

For causal inference, we restricted the sample to journals indexed in the Science Citation Index Expanded (SCIE) of the Journal Citation Reports (JCR), excluding those that were fully OA at inception. The final sample includes 299 journals, of which 26 transitioned from subscription-based to full and immediate OA during the study period (treatment group), while 273 remained hybrid journals publishing both OA and closed articles.

In total, as of May 6, 2025, we collected 1,041,761 articles ("Articles" and "Review Articles"), with 31.07% classified as OA. Article-level OA status was determined using WoS indicators. Journal-level OA reforms and transition years were identified from the *Directory of Open Access Journals* (DOAJ) and cross-validated with JCR. This combined information forms the institutional basis for our DID analyses.

To measure the flow of scientific outputs into technological systems, we utilize patent-to-paper citation data from the Derwent Innovation Index (DII). This database systematically records explicit citations from patents to academic publications across jurisdictions, enabling effective identification of whether and when scientific knowledge has been absorbed by technological actors and manifested in patented innovations.

Additional journal-level metrics, including impact factor, are obtained from the JCR database. Furthermore, the InCites platform provides several article- and journal-level control variables, including field-normalized citation impact, citation counts excluding self-citations, cited half-life, and other journal profile indicators. The dataset was last updated on April 29, 2025, and includes Web of Science indexing records up to March 31, 2025. Given the data availability of some control variables, we have restricted the final estimation period to 1990–2024.

4.2 | Variables

In this section, we provide a detailed introduction to the variables used in our analysis. The definitions, abbreviations, data sources, and relevant descriptive statistics are presented in Table A1 in Appendix A.

4.2.1 | Dependent variable

The core dependent variable in this study is the average number of patent citations per article per journal per year (*patentper*), which serves as a proxy for the extent to which scientific publications are absorbed into technological systems. In essence, if OA improves the accessibility of research outputs—particularly for technological users—this should be reflected in a higher frequency of patent citations to journal articles.

This measure has been widely used in prior studies to evaluate the degree of knowledge transfer from science to technology at the levels of research institutions, academic disciplines, and national innovation systems (Callaert et al., 2006; Verbeek et al., 2002).

4.2.2 | Explanatory variables

The core explanatory variables are designed to align with two distinct empirical strategies: one descriptive and one causal.

At the descriptive (phenomenon-level) stage, the key explanatory variable is Open Access status (OA) at the article level. For each journal-year, articles classified as OA are assigned a value of 1, while non-OA articles are assigned 0. This allows us to compare average patent citations per article between OA and non-OA publications within the same journal and year, minimizing confounding due to journal or time-specific effects.

For the causal identification analysis at the journal level, the main explanatory variable is OAdid, a binary indicator for whether a journal has undergone an open access reform. Specifically, OAdid equals 1 for journal-year observations following the transition from a subscription-based model to full OA publishing, and 0 for journal-years prior to the reform or for journals that never implemented such reform.

4.2.3 | Mechanism variables

At the mechanism level, we introduce two pathway variables to explore how OA facilitates the translation of scientific outputs into technological applications through multiple channels.

The first variable is the Altmetric Attention Score (AAS), which measures the overall online attention received by a scientific article across digital platforms. AAS reflects the visibility and diffusion strength of a paper on social media platforms. This variable is aggregated at the journal × year × OA status level. Since AAS includes data from platforms such as X (formerly Twitter), which launched in 2006, we restrict the estimation period to 2007–2024 to ensure consistency and data availability. AAS values are collected from the Altmetric database for all articles, and then aggregated by journal and year to reflect the total online attention per OA status within each journal-year cell.

The second variable, *Mendeley Readers* (Mendeley), measures how often an article is saved to users' personal libraries on Mendeley. Similar to AAS, this variable is constructed at the journal × year × OA status level using article-level data from the Altmetric database, aggregated into annual totals by group.

Mendeley readership has been widely regarded as a valid proxy for early-stage academic usage, as it typically precedes formal citations and correlates with later scholarly impact (Bornmann, 2014; Thelwall, 2018). Importantly, Mendeley coverage extends across disciplines, including applied domains such as agriculture and environmental sciences, ensuring representativeness beyond the core basic sciences (Bornmann, 2014; Zahedi et al., 2014). Moreover, analyses of Mendeley user categories reveal that its readership is not restricted to academic researchers but also includes industry practitioners, R&D staff, and technical consultants (Mohammadi et al., 2015). This diversity of users underscores Mendeley readership as a meaningful indicator of early scholarly interest and potential technological relevance.

While Mendeley readership does not directly capture the application of knowledge in technological contexts, its disciplinary breadth and inclusion of industry-related users indicate that it can reasonably serve as a proxy for early-stage engagement with potential technological relevance.

4.2.4 | Control variables

To enhance the robustness and interpretability of the empirical results, this study incorporates a comprehensive set of control variables.

First, to capture academic citation performance, we include the citation count excluding self-citations (CIT_noSelf) to mitigate inflation due to author self-referencing. Additionally, the field-normalized citation impact (FNCI) is included to account for systematic differences in citation practices across disciplines.

Second, to reflect journal-level academic influence and stability, we control for the Journal Impact Factor (JIF), citation half-life (CHL), Journal Eigenfactor Score (EF), and the percentage of papers cited (PPC). Together, these indicators provide a robust measure of a journal's scholarly reputation and long-term visibility. Specifically, we used the JIF corresponding to each publication year, ensuring that the indicator reflects the contemporaneous impact level of journals in the year of article publication.

Finally, we include the number of papers (NP) published annually by each journal, based on data from the Web of Science (WoS), to account for variation in publication volume, which may affect exposure and, consequently, the likelihood of patent citations.

4.3 | Model specification

To systematically evaluate the impact of OA on the translation of scientific knowledge into technological systems, this study employs a two-stage identification strategy combining descriptive and causal approaches. Regression analysis is used because it allows us to estimate the associations between article-level factors and citation outcomes while controlling for multiple covariates. Unlike ANOVA or Taguchi methods, regression is more appropriate for observational data and for modeling several continuous predictors simultaneously, which aligns with common practice in bibliometric research. All empirical analyses were conducted in Stata version 19.

4.3.1 | Phenomenon-level comparison

We begin by examining whether OA articles demonstrate higher technological translation potential on average. In contrast to previous studies that rely on cross-journal or cross-discipline comparisons, our approach introduces a within–journal–year comparison framework, in which OA and non-OA articles published in the same journal and year are compared directly. This "local counterfactual" design allows us to control for unobserved heterogeneity related to journal reputation, disciplinary citation norms, and time trends, thereby improving the identification precision of OA's potential advantages in technology spillover.

Specifically, we construct a three-dimensional panel at the journal × year × OA status level, calculating the average number of patent citations per article separately for OA and non-OA articles. This aggregated dataset is then used to estimate whether systematic differences exist between the two groups in terms of patent citation outcomes.

Given that the dependent variable represents the average number of patent citations per article for each journal–year under OA and non-OA conditions, and is measured as a continuous variable rather than an integer count, we employ an Ordinary Least Squares (OLS) regression model to estimate the association. The model is specified as follows:

$$PatentPer_{jt} = \alpha_0 + \alpha_1 OA_{jt} + \alpha_2 z_{jt} + \mu_j + \lambda_t + \epsilon_{jt} \quad (1)$$

In this model, $PatentPer_{jt}$ denotes the average number of patent citations per article for journal j in year t, separately calculated for OA and non-OA publications. The key explanatory variable, OA_{jt}, is a binary indicator equal to 1 if the group represents open access articles, and 0 otherwise. Although Equation (1) uses OA_{jt} at the journal-year level, in practice the unit of analysis is *journal × year × OA status*. For hybrid journals, OA and non-OA articles are separated within the same year, and outcomes are aggregated by status. This approach ensures accurate representation of OA variation without misclassifying hybrid journals. The specification includes journal fixed effects (μ_j) to account for time-invariant journal-specific characteristics, and year fixed effects (λ_t) to control for global temporal shocks and citation trends.

A set of time-varying control variables Z_{jt}, as defined in Section 4.2, is also included to account for heterogeneity in journal-level citation performance, scientific influence, and publication volume. The error term ε_{jt} captures residual variation unexplained by observed factors. Robust standard errors clustered at the journal level are used to ensure reliable statistical inference. To ensure robustness, we also estimate a negative binomial model using the original citation counts.

4.3.2 | Causal identification

Baseline DID model

We employ a quasi-natural experiment design to identify the causal effect of OA reform on the flow of scientific knowledge into technology. Journal-level OA transitions serve as exogenous policy shocks, mitigating concerns of self-selection bias at the article level. Compared with cross-sectional difference analysis, the multi-period DID method enables more precise identification of changes before and after OA policy implementation. By incorporating both journal and year fixed effects, this approach effectively reduces the risk of confounding from unobserved heterogeneity and common temporal trends, thereby enhancing the rigor of causal inference.

In this part, we divide the sample into a treatment group and a control group. The treatment group consists of 26 journals that transitioned from a subscription-based model to a fully OA model. The distribution of transition years for these 26 journals is reported in Table B1 in Appendix B. To maintain treatment purity, we classify only non-OA articles prior to the reform year and only OA articles thereafter—where OA includes all forms of OA—as belonging to the treatment group. The control group comprises 203 journals that did not undergo any full OA transition during the observation period (1990–2024). For consistency, we restrict the control group to non-OA articles only, thereby ensuring structural comparability and avoiding contamination from mixed publishing models.

The baseline DID regression model is specified as follows:

$$PatentPer_{jt} = \beta_0 + \beta_1 OAdid_{jt} + \beta_2 X_{jt} + \mu_j + \lambda_t + \epsilon_{jt} \quad (2)$$

$OAdid_{jt}$ is a binary indicator equal to 1 if journal j has entered the post-OA reform period in year t, and 0 otherwise. The coefficient of interest, β_1, captures the average treatment effect of OA reform on the rate at which scientific articles are cited by patents. A statistically significant and positive β_1 would suggest that journal-level OA reform facilitates the translation of scientific knowledge into technological outputs. X_{jt} represents a vector of control variables at the journal-year level (including journal impact factor, publication volume, cited half-life, etc.), and β_2 denotes the associated coefficients.

Parallel trend test

A fundamental identification assumption of the DID approach is that, prior to the policy intervention, the treatment and control groups exhibit parallel trends in the outcome variable. To test this assumption, we adopt an event study design following the approach of Jacobson et al. (1993), which enables both visual inspection and statistical testing of dynamic differences in patent citation outcomes between treated and untreated journals over time.

Specifically, we recode the time axis into event time, centered around each journal's OA reform year. A series of relative year dummies are constructed to indicate the timing of each journal-year observation with respect to its reform year. These are then included in the following extended model:

$$PatentPer_{jt} = \alpha + \sum_{k=-5}^{6} \delta_k D_{jt}^{(k)} + \beta X_{jt} + \mu_j + \lambda_t + \epsilon_{jt} \quad (3)$$

In Equation (3), $D_{jt}^{(k)}$ is a dummy variable that equals 1 if journal j in year t is in the k period relative to its OA reform year, and 0 otherwise. The coefficients δ_k capture the dynamic treatment effects, representing the difference in average patent citations between the treatment and control groups in period k, relative to the base year. X_{jt} represents a vector of control variables at the journal-year level (including journal impact factor, publication volume, cited half-life, etc.), and β denotes the associated coefficients.

To account for data sparsity in extreme years, we collapse all pre-reform years earlier than -5 into a single category $k=-5$, and post-reform years beyond $+6$ into $k=6$. The base period is set to $k=-5$, that is, 5 years before the reform. This approach addresses the sparsity of observations in distant pre-treatment years, prevents inflated standard errors, and follows standard practice in event-study designs (Jacobson et al., 1993).

If the estimated values of δ_k for $k<0$ are statistically insignificant, this provides support for the parallel trends assumption. Conversely, if the δ_k estimates for $k \geq 0$ are significantly positive and consistent with theoretical expectations, this suggests that OA reform led to a significant improvement in patent citation performance among treated journals.

This event study framework not only offers a transparent visual check of the parallel trends assumption but also provides insights into the dynamic treatment path, strengthening the interpretation of OA reform effects as causal.

Controlling for time trends

To ensure that the estimated policy effects are not confounded by underlying temporal trends, we follow the approach of Li et al. (2016) by including a linear time trend variable t in the baseline DID model. The extended specification is as follows:

$$PatentPer_{jt} = \beta_0 + \beta_1 OAdid_{jt} + \beta_2 t + \beta_3 X_{jt} + \mu_j + \lambda_t + \epsilon_{jt} \quad (4)$$

To further address potential bias from long-run trends or journal-specific developments, we adopt a more flexible specification inspired by Moser and Voena (2012). Specifically, we include interactions between each journal and the time trend, allowing for heterogeneous temporal dynamics across journals. The resulting specification is:

$$PatentPer_{jt} = \beta_0 + \beta_1 OAdid + \beta_2 J_j \times t + \beta_3 X_{jt} + \mu_j + \lambda_t + \epsilon_{jt} \quad (5)$$

5 | RESULTS

5.1 | Phenomenon-level results

We estimate a OLS model to test whether OA articles are more likely to be cited by patents. Table 1 reports the results. In column (1), the OA coefficient is 0.019 and significant at the 5% level, indicating that OA articles receive more patent citations than non-OA articles. In column (2), adding year fixed effects and controls leaves the OA coefficient significant. Columns (3) and (4), which successively add journal fixed effects and additional controls, also yield positive and significant OA coefficients.

TABLE 1 Baseline regression results (phenomenon level).

Variables	(1) *patentper*	(2) *patentper*	(3) *patentper*	(4) *patentper*
oa	0.019**	0.034**	0.034**	0.035**
	[0.023]	[0.018]	[0.024]	[0.021]
	(0.008)	(0.014)	(0.015)	(0.015)
Constant	0.080	0.238***	0.244*	0.225
	[0.105]	[0.000]	[0.078]	[0.123]
	(0.049)	(0.050)	(0.138)	(0.146)
Control	No	Yes	Yes	Yes
N	12,400	5922	5922	5922
R-squared	0.024	0.021	0.054	0.060
Year FE	No	Yes	No	Yes
Journal FE	No	No	Yes	Yes

Note: Standard errors in parentheses, the *p*-values in square brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

These findings support Hypothesis 1 (H1): compared with non-OA articles, OA publications are more frequently cited by patents, demonstrating that OA facilitates the translation of scientific knowledge into technological applications.

To further verify the robustness of the positive association between OA and the translation of scientific outputs into technological systems observed in the baseline regression, we conduct three categories of robustness tests: (1) narrowing the estimation time window, (2) controlling for journal-specific time trends, (3) changing the model specification, and (4) adding the share of internationally co-authored articles to account for collaboration-related factors. The results are summarized in Table C1 in Appendix C. Overall, the robustness checks confirm that our baseline findings are stable and reliable.

5.2 | Causal results

5.2.1 | Baseline regression results

To identify the causal effect of OA on science-to-technology knowledge transfer, we employ a DID strategy leveraging the exogenous timing of OA reforms among agricultural journals.

Table 2 reports the baseline results. In column (1), controlling for year fixed effects, the OAdid coefficient is 0.062 and significant at the 5% level, indicating a rise in patent citations per article post-OA transition. Columns (2) to (4) add control variables, journal fixed effects and adopt a random effects specification; across all models, the OAdid coefficient remains positive and stable, supporting the hypothesis that OA reform enhances technological uptake of research.

A Hausman test $\chi^2(22) = 60.10$, corrected for non-positive definite covariance using the sigmamore adjustment, rejects the random effects model, confirming fixed effects as more appropriate.

Overall, the DID results demonstrate that OA reforms causally increase patent citations, underscoring that OA not only boosts visibility but strengthens knowledge spillovers to technological domains, supporting H1.

5.2.2 | Parallel trend test

To validate the DID identification strategy, we conduct an event study to test the parallel trend assumption. Figure 2 plots estimated coefficients and 95% confidence intervals across relative time periods.

In the pre-reform period (years −4 to −1), all coefficients are statistically indistinguishable from zero, supporting the parallel trend assumption essential for causal inference.

Post-reform (years 0–6), treatment effects gradually increase. By year 2, the coefficient reaches ~0.14 and is statistically significant, indicating a growing OA impact on patent citations. While confidence intervals widen in later years, most post-treatment estimates remain above pre-reform levels, reinforcing the DID results.

Sample size declines over time: all 26 journals contribute in year 1, falling to 24 in year 2, 23 in year 3, and 17 by year 5. This attrition explains the wider confidence intervals in later periods.

Overall, the event study confirms the validity of the DID design and illustrates the dynamic effects of OA reforms on the technological relevance of scientific outputs.

TABLE 2 Baseline DID regression results.

Variables	(1) *patentper*	(2) *patentper*	(3) *patentper*	(4) *patentper*
OAdid	0.062**	0.021***	0.035**	0.017*
	[0.014]	[0.005]	[0.022]	[0.090]
	(0.025)	(0.007)	(0.015)	(0.010)
Constant	0.117***	0.158***	0.121***	0.075***
	[0.000]	[0.000]	[0.000]	[0.000]
	(0.025)	(0.025)	(0.021)	(0.015)
Control	No	Yes	Yes	Yes
N	5616	2644	2644	2644
R-squared	0.087	0.471	0.260	0.2715
Number of j	229	224	224	224
Year FE	Yes	No	Yes	
Journal FE	No	Yes	Yes	
Year RE				Yes
Journal RE				Yes

Note: Standard errors in parentheses, the *p*-values in square brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

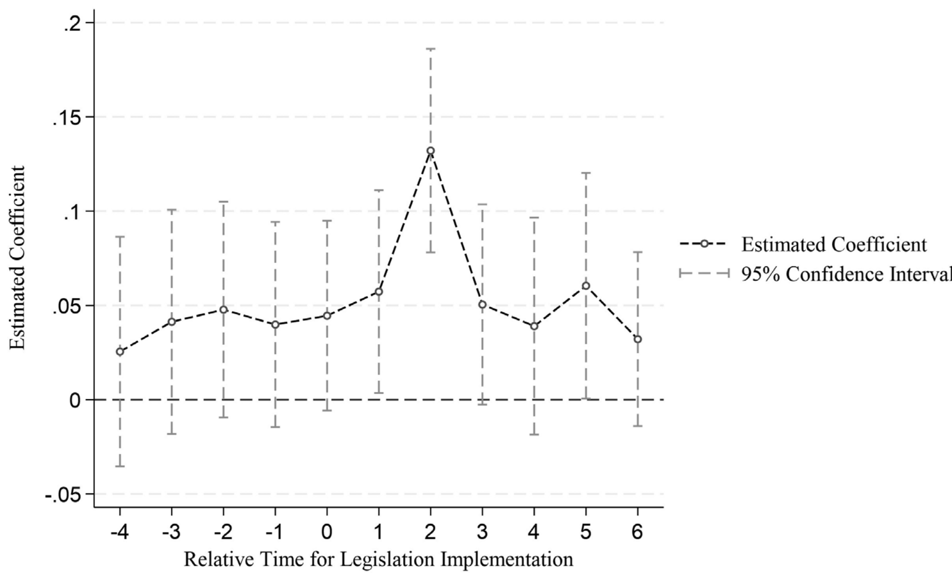

FIGURE 2 Event study estimates for parallel trend test.

5.2.3 | Robustness and causal identification checks

To ensure the validity of our causal identification strategy, we conduct a series of robustness checks, including placebo tests, controls for non-parallel trends, alternative specifications, and the inclusion of additional collaboration-related covariates. Due to space constraints, the full results and technical details are reported in Appendix D.

In summary, the placebo test confirms that the estimated policy effect is unlikely to be driven by random shocks or model artifacts. The results remain robust after controlling for both global and journal-specific time trends. Additional checks using alternative dependent variables, model specifications, sample periods, and outlier treatments consistently support the positive and significant impact of OA reform on patent citations. Moreover, incorporating the share of internationally co-authored articles as an additional control variable shows that the estimated effect remains positive and statistically significant, indicating that cross-border collaboration patterns do not drive the observed relationship. Taken together, these findings reinforce the credibility of the DID estimates and strengthen the causal interpretation.

TABLE 3 Effects of OA reform on social media attention and scholarly usage.

Variables	(1) *AAS*	(2) *AAS*	(3) *Mendeley*	(4) *Mendeley*
OAdid	109.540**	123.042**	1278.839***	983.892**
	[0.019]	[0.034]	[0.004]	[0.038]
	(46.553)	(58.1085)	(443.624)	(475.023)
Constant	−33.018	−56.440	−340.498	1020.085
	[0.471]	[0.479]	[0.435]	[0.117]
	(45.752)	(79.672)	(435.988)	(651.300)
Control	No	Yes	No	Yes
N	5616	2644	5616	2644
R-squared	0.026	0.106	0.072	0.454
Number of j	229	224	229	224
Year FE	Yes	Yes	Yes	Yes
Journal FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, *p*-values in square brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

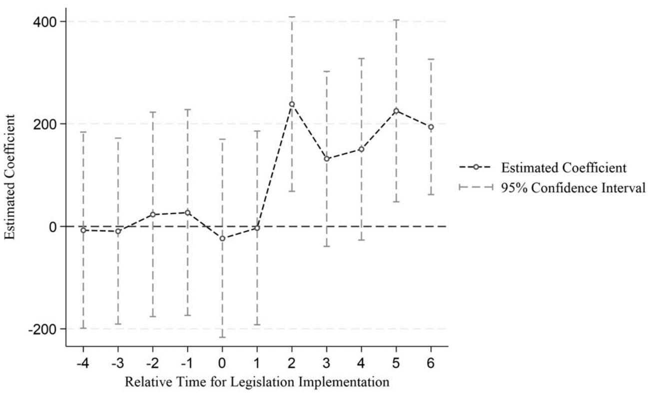

FIGURE 3 Parallel trend test: Effect of OA reform on social media attention (Altmetric Attention Score).

5.3 | Mechanism analysis: Pathway identification

To examine the mechanisms through which OA reform promotes science-to-technology translation, we adopt a path decomposition strategy Di Giuli and Laux (2022), combining first-stage mediator effects with theory-informed second-stage outcomes. We focus on two mediators: the AAS and Mendeley Readers, proxies for digital visibility and scholarly engagement, respectively.

Using a multi-period DID framework, we estimate the effect of OA reform on each mediator. Table 3 shows that OA significantly increases both AAS and Mendeley readership. In all specifications, the OAdid coefficient is positive and statistically significant supporting the hypothesis that OA enhances online attention and early academic uptake.

These findings suggest that OA reforms boost the visibility and usability of scientific outputs, establishing a structural pathway through which research reaches technological audiences.

To validate the DID identification for these mediators, we conduct parallel trend tests for both outcomes. Results (Figures 3 and 4) confirm no significant pre-reform differences between treated and control groups, supporting the causal interpretation of the mechanism pathway.

6 | CONCLUSION AND DISCUSSION

6.1 | Conclusion

This study examines the impact of OA on the translation of scientific knowledge into technological systems using SCI-indexed agricultural journals.

First, OA articles are significantly more likely to be cited by patents, indicating enhanced technological applicability.

Second, this effect is causal and robust, confirmed by placebo tests and parallel trend analyses.

Third, OA facilitates knowledge transfer both directly—by removing access barriers—and indirectly—by increasing online visibility (AAS) and scholarly engagement (Mendeley Readers).

Overall, the findings provide strong empirical evidence for the causal role of OA in science-to-technology translation and reveal multiple mechanisms underpinning this process, offering new insights into OA's function in the innovation system.

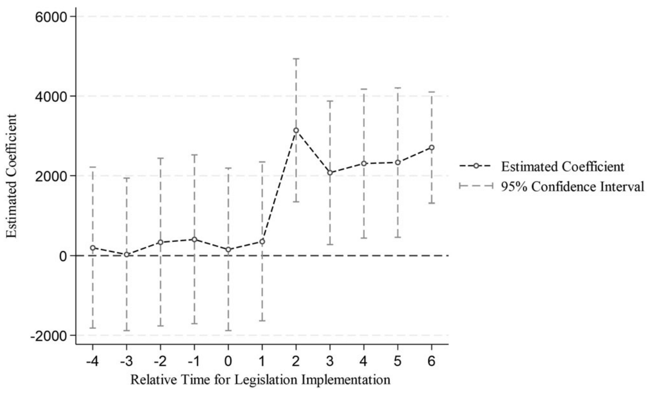

FIGURE 4 Parallel trend test: Effect of OA reform on scholarly usage (Mendeley Readers).

6.2 | Discussion

This study advances the literature on OA and the translation of scientific knowledge into technological systems by offering both theoretical depth and empirical rigor. It presents a forward-looking theoretical perspective by framing OA not merely as a scholarly communication model, but as a policy-relevant institutional mechanism that enhances the technological relevance of scientific research. This reframing positions OA within the broader context of innovation policy and science governance.

From the perspective of knowledge spillover theory (Arrow, 1962; Romer, 1990), our results confirm that OA reduces access barriers and thereby strengthens the first precondition for knowledge transfer—information accessibility. While OA cannot by itself guarantee comprehension or absorptive capacity, the observed increase in patent citations suggests that lowering the access barrier is nonetheless a necessary institutional step toward enabling downstream knowledge use.

Second, the findings support the digital attention mechanism, showing that OA articles attract higher Altmetric Attention Scores, which indicates broader visibility across digital and social platforms. The evidence is consistent with diffusion of innovation theory: early visibility increases the likelihood that knowledge is noticed and potentially reused in later technological contexts.

Third, the results highlight the role of scholarly usage mechanisms, as proxied by Mendeley readership. OA articles demonstrate higher levels of early-stage academic engagement, and prior research shows that Mendeley readership is correlated with both future scholarly impact and diverse user groups including practitioners (Mohammadi et al., 2015). This pathway underscores the multidimensional nature of OA's impact on knowledge flows, linking early engagement to potential technological uptake. It is important to note that the mechanism we discuss is not proposed as a dominant or complete pathway. The presence of technical users on platforms such as Mendeley is limited but non-negligible.

Consistent with prior bibliometric and scientometric research, the relatively low R-squared values reflect the high dispersion and inherent noise in article-level citation and patent citation data. Our aim is to estimate marginal associations rather than to achieve high predictive power, and low R-squared values do not undermine the validity of the estimated coefficients.

In sum, by embedding empirical results within the proposed theoretical framework, the study demonstrates that OA functions as an institutional mechanism that lowers access costs, amplifies digital visibility, and enhances scholarly usage—together facilitating the spillover of science into technology.

6.3 | Policy implications

These findings highlight that OA is not merely an access tool, but a strategic mechanism for amplifying the societal and technological impact of science. By combining causal identification with mechanism-based evidence, this study positions OA as a core component of modern science and innovation governance.

Several policy implications follow. First, OA should be recognized as an institutional tool for increasing the social return on public investment in basic science, by facilitating the flow of research into patents and industrial applications. To realize this potential, research funding agencies may implement mandatory OA requirements for publicly funded outputs and offer targeted subsidies to support journals in transitioning from subscription-based to hybrid or full OA models. Such efforts would reduce access barriers while promoting a more open and innovation-friendly publishing environment.

Second, because OA operates through multiple spillover channels—such as boosting digital visibility and enhancing academic usage—it should not be treated solely as a publishing reform. Instead, OA policies should be embedded in a broader innovation ecosystem, supporting the development of research-sharing platforms, altmetric infrastructures, and digital scholarly tools. Enhancing the interoperability and accessibility of these systems can maximize the systemic benefits of OA, accelerating knowledge circulation across institutional, disciplinary, and sectoral boundaries.

6.4 | Limitations and future directions

Despite its contributions, this study has limitations. It focuses on agricultural sciences, which may limit generalizability. Patent citations may also reflect time-lag effects, especially in emerging fields. Additionally, we do not differentiate by patent type, assignee, or technological domain—dimensions that future research could explore to refine understanding of OA's impact. And the study was not pre-registered, which should be acknowledged as a limitation in terms of research transparency.

A further limitation concerns the AAS, which includes patent mentions. This overlap may partially conflate the mediator with the outcome. Although we interpret AAS as a proxy for digital visibility, caution is warranted. Future studies could use alternative visibility metrics excluding patent mentions.

AUTHOR CONTRIBUTIONS

Pengfei Jia: Conceptualization, formal analysis; writing—original draft. **Weixi Xie**: Investigation; methodology. **Guangyao Zhang**: Formal analysis; data curation. **Xianwen Wang**: Conceptualization; writing—review and editing; funding acquisition; validation.

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CONFLICT OF INTEREST STATEMENT

No potential conflict of interest was reported by the authors.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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APPENDIX A

In the descriptive statistics, different strategies were adopted for categorical and ordinal variables. Since OA status and OAdid are categorical variables, we additionally report the sample counts and proportions of each category (0/1). For the OA variable, out of 12,778 observations, 1 accounts for 45.41%, while 0 accounts for 54.59%. For the OAdid variable, among 6561 observations, 1 accounts for 4.34%.

In contrast, the Journal Impact Factor (JIF) is an ordinal variable. Therefore, we additionally report its quartiles. The 25th, 50th (median), and 75th percentile values of JIF are 0.609, 1.115, and 1.900, respectively, which better reflect the distribution of journal impact across the sample.

TABLE A1 Variable definitions and descriptive statistics.

Category	Variable (Abbr.)	Definition	Source	Mean	SD	Min	Max
Dependent Variable	Average Patent Citations per Paper (patentper)	Average number of times articles are cited by patents, per journal-year	WoS, Derwent Innovation Index	0.083	0.463	0	37
Main Explanatory Variables	Open Access Status (oa)	Equals 1 if an article is OA at publication; 0 otherwise	WoS	0.043	0.204	0	1
	OA Reform Indicator (OAdid)	Equals 1 if a journal has transitioned to full OA in a given year	DOAJ	0.454	0.498	0	1
Mechanism Variables	Altmetric Attention Score (AAS)	Total digital attention score across platforms (e.g., X, blogs, NEWS)	Altmetric.com	103.546	454.075	0	23,105
	Mendeley Readers (Mendeley)	Number of users who saved the article in Mendeley (proxy for early usage)	Altmetric.com	1587.191	5260.332	0	131,903
Control Variables	Citation Count Excluding Self-Citations (CIT_noSelf)	Total citations excluding self-citations	InCites	2279.499	6291.151	0	108,320
	Field-Normalized Citation Impact (FNCI)	Citation performance adjusted by field norms	InCites	0.807	0.695	0	19
	Journal Impact Factor (JIF)	2-year average citations per article in a journal	Journal Citation Reports	1.891	21.318	0	11.452
	Citation Half-Life (CHL)	Median age of cited articles in a journal	InCites	7.690	3.091	1.2	33.4
	Journal Eigenfactor Score (EF)	Influence measure based on weighted citation networks	InCites	0.005	0.011	0	0.1335
	Percentage of Papers Cited (PPC)	Proportion of articles that have received at least one citation	InCites	81.086	26.713	0	100
	Number of Papers Published (NP)	Total number of articles published per journal-year	WoS	111.161	193.027	1	3022

APPENDIX B

TABLE B1 Transition years of the 26 journals to full OA.

Year	Count	Year	Count
1999	1	2014	2
2002	1	2015	2
2003	1	2016	2
2004	1	2018	2
2005	1	2019	1
2009	1	2020	5
2010	1	2022	1
2012	2	2023	2

Note: The table reports the distribution of transition years for the 26 journals that shifted from subscription-based to full OA publishing models during 1999–2023.

APPENDIX C

C.1 | PHENOMENON-LEVEL ROBUSTNESS TEST

First, we restrict the estimation period from 1990–2024 to 2011–2024 to test whether early-year observations affect the baseline results. As shown in column (1), the coefficient on OA remains positive and statistically significant at the 1% level. In column (2), after adding control variables, the OA coefficient continues to be positive and significant, indicating that the result is not sensitive to changes in the time frame.

Second, to address potential systematic differences in patent citation trends across journals, we control for journal-specific linear time trends by including journal × year interaction terms (i.e., c.j × c.year). In columns (3) and (4), the OA coefficient remains positive and significant, suggesting that the observed OA advantage is not driven by idiosyncratic trends at the journal level.

Third, we re-estimate the model using a Negative Binomial regression framework to test whether the results are sensitive to model specification. To make the dependent variable suitable for count-data modeling, we discretized the average number of patent citations per article by rounding it to the nearest integer. As shown in columns (5) and (6), the OA coefficients remain statistically significant and consistent in direction with the baseline results.

Finally, to further mitigate concerns regarding omitted variable bias related to collaboration patterns, we incorporate the share of internationally co-authored articles as an additional control variable. International collaboration is a well-documented predictor of both scientific impact and technological relevance. Columns (7) and (8) show that the inclusion of this variable leaves the *OA* effect positive and statistically significant. This indicates that the estimated OA–patent citation relationship is not driven by unobserved collaboration patterns and reinforces the robustness of our findings.

Overall, these robustness tests provide further empirical support for the conclusion that OA articles are more likely to be absorbed into technological systems, reinforcing the findings presented in support of H1.

TABLE C1 Robustness test results (phenomenon level).

Variables	(1) *patentper*	(2) *patentper*	(3) *patentper*	(4) *patentper*	(5) *patentper*	(6) *patentper*	(7) *patentper*	(8) *patentper*
oa	0.019***	0.013**	0.025*	0.035**	0.599***	1.180***	0.019**	0.019*
	[0.000]	[0.023]	[0.079]	[0.022]	[0.000]	[0.001]	[0.021]	[0.064]
	(0.005)	(0.006)	(0.014)	(0.015)	(0.188)	(0.335)	(0.335)	(0.010)
c.j × c.year			Yes	Yes				
Constant	0.040	0.133**	0.020	0.229*	−3.575***	−4.711***	0.010	0.184
	[0.312]	[0.037]	[0.583]	[0.099]	[0.006]	[0.000]	[0.335]	[0.130]
	(0.039)	(0.064)	(0.037)	(0.139)	(0.587)	(1.715)	(0.011)	(0.121)
Control	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	6428	4976	5922	5922	12,400	5922	5922	5922
R-squared	0.094	0.098	0.010	0.054			0.012	0.065
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Journal FE	Yes	Yes	No	Yes	Yes	Yes	No	Yes

Note: Standard errors in parentheses, *P*-values in square brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

APPENDIX D

D.1 | PLACEBO TEST

To further validate the causal interpretation of the DID estimates, we conduct a placebo test. This method helps to rule out the possibility of spurious causality due to model mis-specification, structural features of the data, or underlying time trends. It ensures that the observed treatment effect is not driven by artifacts in the estimation procedure.

Figure D1 presents the results of the placebo test. In this analysis, we simulate 500 iterations of the DID model using randomly assigned placebo OA reform years for the treatment group. The red dots represent the distribution of estimated treatment effects under these placebo assignments, while the black line shows the kernel density of those estimates. As shown, most placebo estimates are tightly concentrated around zero and are substantially smaller than the true DID estimate, indicated by the vertical dashed line.

From a probabilistic perspective, the majority of placebo coefficients exhibit *p*-values between 0.1 and 1, suggesting insignificance. In contrast, the true DID estimate lies in the far right tail of the placebo distribution and is well beyond the central tendency of the simulated effects. This strongly reinforces the credibility of the observed policy effect and reduces the likelihood that the result is due to confounding factors such as field-specific trends or changes in patenting systems.

Specifically, fewer than 5% of placebo estimates yield *p*-values below the 0.05 threshold, which is consistent with random chance under repeated sampling. By comparison, the actual OA reform effect remains statistically significant and clearly separated from this null distribution.

In sum, the placebo test provides compelling evidence that the positive effect of OA reform on patent citations is not an artifact of timing or model design, but reflects a genuine causal relationship. This strengthens the validity of the DID identification strategy and affirms that OA policies play a meaningful role in facilitating the translation of scientific knowledge into technological outputs.

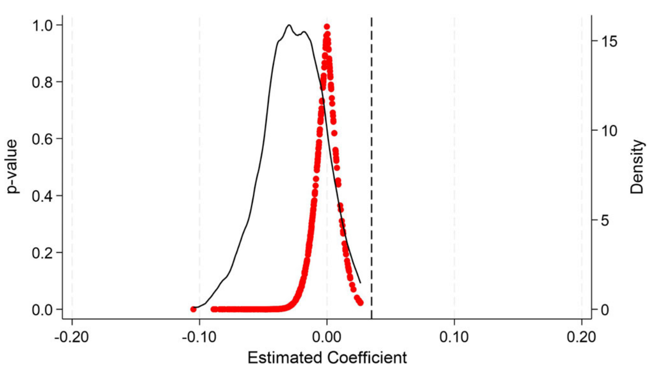

FIGURE D1 Placebo test.

D.2 | CONTROLLING FOR NON-PARALLEL TRENDS

Within the DID identification framework, the parallel trends assumption is central: the treatment and control groups must exhibit similar trajectories in the outcome variable prior to policy implementation. If systematic differences in trends exist between the groups, the estimated policy effect may be biased. Although the event study in Section 5.2.2 provides visual support for this assumption, we further reinforce the credibility of the identification strategy by incorporating explicit trend controls to address potential violations of trend homogeneity.

Specifically, we include two forms of trend controls in the regression models. The first is a global linear time trend (c.year), which accounts for time-varying factors that may influence all journals simultaneously. The second is a set of journal-specific time trends (c.year × c.j), allowing each journal to follow its own linear trajectory over time. This specification captures unobserved heterogeneity arising from factors such as field evolution, editorial policy shifts, or journal repositioning. Compared with traditional fixed effects models, this enhanced design is particularly robust in quasi-experimental settings.

The results are reported in Table D1 Despite the inclusion of more stringent trend controls, the OA policy variable (OAdid) remains positive and statistically significant across all specifications. In column (1), controlling for global trends yields a coefficient of 0.052; in column (3), with journal-specific trends, the effect increases to 0.067. In columns (2) and (4), after introducing the full set of control variables, the coefficients remain stable and significant.

These findings confirm that the observed policy effect is not driven by pre-existing trend differences between groups. By incorporating both global and journal-level time trends, we effectively mitigate concerns about non-parallel trends and strengthen the causal interpretation of the DID estimates. The results suggest that the observed increase in patent citations is attributable to institutional OA reform, not spurious temporal dynamics.

D.3 | ROBUSTNESS TESTS FOR CAUSAL IDENTIFICATION

To further validate the robustness of the DID estimates regarding the effect of OA policy reform, we conduct a

TABLE D1 DID regression results with time trend controls.

Variables	(1) *patentper*	(2) *patentper*	(3) *patentper*	(4) *patentper*
OAdid	0.052**	0.044***	0.067***	0.040***
	[0.040]	[0.003]	[0.007]	[0.008]
	(0.025)	(0.015)	(0.025)	(0.015)
c.year×c.j			YES	YES
C.year	YES	YES		
Constant	13.615***	12.465***	3.930***	5.824***
	[0.000]	[0.000]	[0.001]	[0.000]
	(0.734)	(1.462)	(1.199)	(1.301)
Control	No	Yes	No	Yes
N	5616	2644	5616	2644
R-squared	0.060	0.242	0.089	0.266
Number of j	229	224	229	224
Year FE	Yes	Yes	Yes	Yes
Journal FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, p-values in square brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE D2 Robustness checks for DID estimates.

Variables	(1) *patent*	(2) *patent*	(3) *patentper*	(4) *patentper*	(5) *patentper*	(6) *patentper*
OAdid	17.175**	11.643*	1.069***	1.069***	0.067**	0.035**
	[0.016]	[0.081]	[0.000]	[0.000]	[0.011]	[0.022]
	(7.106)	(6.671)	(0.268)	(0.268)	(0.026)	(0.015)
Constant	15.137**	25.002***	−30.067***	−22.783***	0.289***	0.121***
	[0.030]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(6.983)	(4.450)	(1.380)	(1.390)	(0.020)	(0.021)
Control	No	Yes	Yes	Yes	No	Yes
Observations	5616	3222	2644	2644	4553	2644
R-squared	0.030	0.066			0.095	0.260
Number of j	229	226	224	224	228	224
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Journal FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, p-values in square brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

series of multi-dimensional robustness checks, as reported in Table D2 and D3.

First, we replace the dependent variable with the total number of patent citations (patent), rather than average citations per article. In column (1), OA reform is associated with an increase of approximately 17.175 patent citations per journal-year, significant at the 5% level. After adding control variables in column (2), the coefficient remains positive and statistically significant, suggesting that OA reform not only enhances the likelihood of individual articles being cited but also amplifies the overall technological impact of journals.

Second, considering that patent citations are count data, we re-estimate the DID model using a Negative Binomial specification. As shown in columns (3) and (4), the OA reform coefficient remains positive and significant across both model variants.

Third, to test for sensitivity to the temporal scope, we shorten the sample period from 1990–2024 to 2000–2024. The results in columns (5) and (6) remain stable and

TABLE D3 Supplementary robustness checks for the DID.

Variables	(7) *patentper*	(8) *patentper*	(9) *patentper*	(10) *patentper*	(11) *patentper*	(12) *patentper*
OAdid	0.052***	0.033**	0.037***	0.029***	0.021**	0.035***
	[0.001]	[0.020]	[0.000]	[0.001]	[0.045]	[0.009]
	(0.015)	(0.014)	(0.008)	(0.009)	(0.010)	(0.013)
Constant	0.107***	0.120***	0.071***	0.091***	0.0178***	0.120***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.015)	(0.020)	(0.008)	(0.012)	(0.032)	(0.033)
Control	No	Yes	No	Yes	Yes	Yes
Observations	5616	2644	5616	2644	2644	2644
R-squared	0.145	0.274	0.206	0.315	0.220	0.260
Number of j	229	224	229	224	224	224
Year FE	Yes	Yes	Yes	Yes	No	Yes
Journal FE	Yes	Yes	Yes	Yes	No	Yes

Note: Standard errors in parentheses, p-values in square brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

robust, indicating that the main findings are not driven by early-period observations.

Fourth, to mitigate the influence of extreme outliers, we conduct winsorization of the dependent variable at the 1% and 5% levels, respectively. Results in columns (7) through (10) show that the OA reform variable continues to yield positive and significant coefficients, further supporting the robustness of the causal effect.

Finally, we incorporate the share of internationally co-authored articles as an additional control variable to account for collaboration-related factors that may simultaneously influence OA adoption and patent citations. Columns (11) and (12) show that the OA reform coefficient remains positive and significant after including this variable, demonstrating that the estimated effect is not attributable to unobserved collaboration patterns. This additional check further reduces concerns about omitted variable bias.

Taken together, the consistency of these results across multiple robustness checks confirms the credibility and reliability of the DID estimates. OA policy reform has a stable and positive impact on the translation of scientific outputs into technological applications, as reflected by patent citations.

APPENDIX E

To enhance the transparency and reproducibility of our empirical analysis, we provide the complete results of the baseline regression, including the full set of coefficients for all control variables. These extended tables allow readers to examine the detailed parameter estimates underlying the main findings. The full results are reported in Table E1 in Appendix E.

TABLE E1 Full baseline regression results with all control variables.

VARIABLES	(1) *patentper*	(2) *patentper*	(3) *patentper*	(4) *patentper*
oa	0.019**	0.034**	0.034**	0.035**
	[0.023]	[0.018]	[0.024]	[0.021]
	(0.008)	(0.014)	(0.015)	(0.015)
PPC	—	0.000	0.000	0.001
	—	[0.279]	[0.486]	[0.265]
	—	(0.000)	(0.000)	(0.000)
CIT_noSelf	—	0.000**	−0.000	0.000*
	—	[0.034]	[0.390]	[0.065]
	—	(0.000)	(0.000)	(0.000)
FNCI	—	−0.002	−0.014	−0.016
	—	[0.846]	[0.327]	[0.327]
	—	(0.013)	(0.016)	(0.016)
CHL	—	−0.003	−0.005	−0.005
	—	[0.880]	[0.477]	[0.477]
	—	(0.002)	(0.007)	(0.007)
EF	—	0.003	−2.442	−1.107
	—	[0.655]	[0.238]	[0.596]
	—	(0.954)	(2.263)	(2.090)
JIF	—	0.013	−0.010	−0.012
	—	[0.847]	[0.398]	[0.398]
	—	(0.007)	(0.012)	(0.012)
NP	—	−0.000*	−0.000*	−0.000*
	—	[0.067]	[0.076]	[0.066]
	—	(0.000)	(0.000)	(0.000)
Year FE	No	Yes	No	Yes
Journal FE	No	No	Yes	Yes
N	12,400	5922	5922	5922
R-squared	0.024	0.021	0.054	0.060
Constant	0.080	0.238***	0.244*	0.225
	[0.105]	[0.000]	[0.078]	[0.123]
	(0.049)	(0.050)	(0.138)	(0.146)

Note: Standard errors in parentheses, *p*-values in square brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.