LOST IN TRANSLATION? SCIENCE COMMUNICATION AND THE COMMERCIAL DIFFUSION OF IDEAS

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Abstract

Despite the potential of scientific knowledge to drive firm performance and innovation, many valuable scientific discoveries remain unexploited. I argue that this underutilization of science could be driven by the complexity of scientific communication. I examine the role of *scientific translation* – communication of complex scientific ideas using accessible, non-technical language – through press releases in helping firms draw on academic science. Using a novel dataset of over 350,000 press releases about scientific papers from the past 25 years and exploiting congestion at university press offices as a source of exogenous variation in press coverage, I find that papers with press releases are over ten times more likely to be cited in firm-owned patents. Rather than increase citations simply through increased attention to focal papers, I find that the impact of press releases is higher for papers that use more specialized language, suggesting an important role for the translation mechanism. The benefits, however, are not uniform across firms; those lacking prior scientific capability gain little from these press releases. Instead, scientific translations complement a firm's existing scientific capabilities and are particularly valuable in helping firms explore insights from scientific sub-fields outside their prior areas of expertise. These findings highlight the importance of accessible scientific communication in bridging the gap between academic research and commercial innovation while also emphasizing the importance of scientific capabilities to effectively leverage *translated* knowledge in distant domains.

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1 Introduction

Scientific knowledge is vital for innovation, firm performance, and economic growth, and yet is underutilized in the economy. The use and exploitation of scientific knowledge by firms has been shown to be a key driver of performance and can boost innovation in a variety of sectors of the economy(Arrow, 1962; Nelson, 1982; Romer, 1990; Kogan et al., 2017). Science acts as a beacon for innovation, guiding inventors and researchers in firms to unexplored territories (Fleming and Sorenson, 2004; Nagaraj and Stern, 2020). Moreover, science can be particularly helpful in identifying and combining distant ideas, leading to the creation of more novel and valuable inventions (Uzzi et al., 2013; Kaplan and Vakili, 2015; Arora et al., 2022; Krieger et al., 2024). However, despite the considerable benefits of scientific knowledge and the openness of the scientific community that emphasizes the sharing of research findings, most scientific knowledge is never used in a commercial setting. For instance, less than 5% of published papers are directly cited in patents (Ahmadpoor and Jones, 2017). Even among papers with high commercialization potential, more than half are never utilized in patenting by firms (Masclans et al., 2023). This raises a significant question: why, despite its potential for commercialization, is scientific knowledge not more extensively utilized in commercial applications?

One key reason why scientific knowledge may be underutilized in commercial applications is its reliance on specialized language and inherent complexity, which can pose considerable barriers to understanding and application. Scientific discourse employs precise and often esoteric terminology designed to communicate complex ideas succinctly among experts (Dudley, 2017; McMahon and Naylor, 2024). While efficient for intra-field communication, the use of specialized language creates communication barriers for firms looking to build upon scientific knowledge and transform it into impactful technologies (Baram-Tsabari et al., 2020; Lucy et al., 2023; Ante, 2021). Moreover, the cumulative and increasingly specialized nature of scientific knowledge further compounds this challenge, making it difficult for inventors and firms to build upon new scientific discoveries without extensive prior knowledge in the field (Jones, 2009). This specialization, while necessary for advancing scientific understanding, can hinder the cross-pollination of ideas across different domains, a process that is often crucial for generating novel innovations (Uzzi et al., 2013; Kaplan and Vakili, 2015).

Given the specialized language and complexity of science, firms must develop capabilities to access and understand new scientific knowledge before they can effectively translate it into commercial gains (Cohen and Levinthal, 1990). Scholars have explored various strategies that firms can use to lower the costs of accessing scientific knowledge, including investments in internal research and development (Rosenberg, 1989; Gambardella, 1992), hiring specialized personnel (Almeida and Kogut, 1999; Hsu et al., 2024), and engaging in collaborations with universities and research institutions (Cockburn and Henderson, 1998; Zucker et al., 2002). These demand-side interventions are crucial as they not only increase firms' awareness of new scientific discoveries but also enhance their ability to understand scientific literature. However, these demand-side interventions are resource-intensive; maintaining an R&D department and hiring experts can be expensive, especially for smaller firms, and even large corporations may struggle to sustain expertise across diverse scientific fields (Arora et al., 2018). Even when firms invest in a scientific labor force, they might find the most useful and impactful scientific ideas in distant fields. Therefore, the challenges around specialized language and complexity remain for firms even when they employ scientific human capital. Given these constraints, the question arises of whether supply-side

interventions by scientists and universities can help translate scientific knowledge and reduce the barriers to accessing it.

In this paper, I explore a novel supply-side channel that could potentially reduce the cost of understanding new scientific knowledge and facilitate its commercial diffusion. Specifically, I argue that the translation of science by universities and academic journals through their science communication initiatives could play an important but hitherto underemphasized role in the commercialization of new scientific discoveries. Science communication is the process through which scientific knowledge, inherently complex, is communicated in a simpler, non-technical language to make it accessible to the general public (Burns et al., 2003; Fischhoff and Scheufele, 2013; Kahan et al., 2017). Scientific communication takes many forms, including coverage of science in the media, press releases from universities about newly emerging research presented in simplified language, and scientists directly communicating their findings to policymakers and the general public.

While all these forms of science communication are important, in this paper, I examine the role of official university press releases about new scientific papers in providing a new supply-side channel through which complex scientific ideas could disseminate beyond the ivory tower and be applied in a commercial setting. Most universities in the U.S. have dedicated Press Information Offices (PIOs) tasked with popularizing recent scientific advancements made by researchers at their institutions (Meredith, 2021). PIOs play a crucial role in the science communication process, acting as intermediaries between the scientific community and the media. These offices, staffed by proficient science communicators, convert complex findings from academic research into clear, non-technical summaries through press releases. Science journalists, whether affiliated with newspapers, magazines, or digital platforms, heavily depend on these press releases to report on new scientific developments (MacLaughlin et al., 2018; Vogler and Schäfer, 2020). Prior research has speculated on the role of press releases in science communication and in enhancing public understanding of science (Meredith, 2021; Autzen, 2014; Granado, 2011), raising the question of whether it could play a similar role in diffusing scientific knowledge to firms. However, there has been little systematic investigation of this supply-side intervention in helping the commercial diffusion of science. Motivated by this gap, this paper seeks to examine the impact of PIO-issued press releases on the commercial diffusion of science.

I develop and test a theory of how supply-side scientific communication affects the diffusion of science to firms. First, I argue that the presence of a press release accompanying scientific discoveries increases their likelihood of being adopted in firms' commercialization efforts, as measured by patent-to-paper citations. This facilitation occurs because scientific communication helps firms overcome the inherent barriers in identifying and understanding new commercially relevant scientific ideas. Further, press releases often provide practical implications of science, signaling its relevance and potential application to firms. Second, while press releases serve to provide quality certification and raise awareness of new scientific advancements—which independently could enhance commercialization—I argue that their influence extends through an additional channel: scientific translation. By presenting complex scientific ideas in a simple language, press releases can reduce the cost of understanding and evaluating new scientific knowledge, which can be particularly helpful in understanding scientific knowledge that is communicated using specialized language. I propose that the impact of press releases on increasing patent-to-paper citations is more pronounced when the underlying scientific paper uses more specialized language.

Third, I examine whether scientific translation complements or substitutes a firm's existing scientific expertise. For firms lacking prior scientific expertise, translation can make complex scientific information more comprehensible. However, these firms may still struggle to build upon scientific advances due to limited scientific capabilities. In contrast, firms with existing scientific expertise can directly engage with technical sources, reducing their need for translation, especially in domains where they possess prior expertise. Yet, developing expertise across all relevant fields is resource-intensive and not an option for all firms. I argue that scientific translation can act as a complement to a firm's existing expertise. Specifically, I propose that scientific translations will particularly benefit firms with prior scientific capabilities when building on advances from fields outside their core areas of expertise.

There are two key challenges in testing the relationship between the press releases and the commercial use of science. First, the lack of systematic, large-scale data linking academic publications to press releases. Second, identifying the causal effect of press coverage on scientific knowledge diffusion to the industry is complicated by selection bias, as high-quality research is more likely to be featured in press releases and used by the industry. To address these challenges, I leverage EurekAlert, a centralized repository operated by the American Association for the Advancement of Science (AAAS), which serves as the primary channel for science communicators and journalists to access official press releases about forthcoming scientific articles. Using a novel machine learning-based matching system, I create a comprehensive dataset of over 350,000 press releases linked to academic publications spanning 25 years. To overcome the identification challenge, I exploit quasi-random variation in PIO workload, noting that institutions have fixed PIO staff while the volume of new science published weekly can fluctuate significantly from week to week. This quasi-random variation in PIO congestion provides an arguably exogenous shift in the likelihood of a paper receiving a press release, allowing me to identify the causal effect of press release coverage on the diffusion of scientific knowledge to commercial applications.

I find that even though science is open and freely available to firms and has great economic value, science communication through press releases has an independent and positive effect on the commercialization of science. In particular, press release coverage leads to a 84% percentage points increase in the likelihood of a paper being cited by industry patents. Second, I find strong evidence that the translation of science by PIOs is an important mechanism. I find that papers that use more specialized language and are potentially less accessible benefit more from press coverage as the press releases translate the key findings into a simpler and more accessible language, enhancing their utility and reach. Third, I find that the teams and firms with prior scientific expertise stand to gain more from press coverage, underscoring how prior knowledge impacts the capacity to leverage new scientific insights. Additionally, I find that firms that have prior expertise in a scientific area do not benefit from scientific translation. However, I find that translations aid such firms in building on knowledge outside their core areas of expertise, where barriers to accessing and understanding new information are higher. Overall, my findings imply that beyond firm-level investments, supply-side interventions by universities, like communication, can help firms in identifying and building on new scientific advances, particularly in domains outside their prior expertise.

The paper makes several contributions. First, it contributes to the literature on the commercialization of science (Jaffe et al., 1993; Belenzon and Schankerman, 2013; Bikard, 2018; Bikard and Fernandez-Mateo, 2022; Marx and Hsu, 2021; Koffi and Marx, 2021; Hsu et al., 2024). While prior literature has emphasized the role of demand-side interventions, including internal R&D, hiring, and collaborations in the commercialization of science, I identify a new supply-side channel – science communication through the press – that can help firms

access and understand new scientific discoveries. This channel is easily accessible to a broader swathe of firms. Along with identifying a new channel, the paper introduces a new mechanism, scientific translation by PIOs, that can reduce the costs firms face in acquiring new scientific knowledge. Second, the paper contributes to the literature on firm capabilities (Cohen and Levinthal, 1990). It emphasizes the importance of prior scientific engagement in a firm's ability to exploit new scientific advances, even after such knowledge is translated. The study demonstrates that while a firm's existing scientific capabilities remain crucial for innovation, scientific translations can play a complementary role. This complementarity stems from scientific translation's ability to facilitate understanding of advances outside a firm's core areas of expertise.

In addition, the paper contributes to a parallel body of work on science communication and media studies (Kiernan, 2003; Fischhoff and Scheufele, 2013; Fischhoff, 2019a; Scheufele and Krause, 2019). While prior literature has theorized about the role of the media in popularizing science, the lack of systematic data and empirical design has largely restricted these investigations to descriptive and correlational analyses (National Academies of Sciences et al., 2017). This is the first study to systematically link scientific publications with their associated press releases, creating a novel dataset to explore how the press affects the dissemination of scientific knowledge. Furthermore, the identification strategy introduced in this paper provides a new methodological approach for investigating other media-related impacts. Lastly, by emphasizing the importance of simplified communication, the paper contributes to the growing body of literature on scientific language and its effects on the evaluation and use of scientific knowledge (Lerchenmueller et al., 2019; Peng et al., 2024; Bikard and Fernandez-Mateo, 2022; McMahon and Naylor, 2024).

2 Theory

2.1 Role of Science in Commercial Innovation

Scientific knowledge is vital for innovation and economic growth (Arrow, 1962; Nelson, 1982; Romer, 1990; Kogan et al., 2017). The use and exploitation of scientific knowledge by firms has been shown to be a key driver of firm performance and can boost innovation in a variety of different sectors of the economy (Cohen et al., 2002; Hall and Rosenberg, 2010; Bloom et al., 2013; Arora et al., 2021). While corporations used to contribute to scientific knowledge through their R&D efforts, this trend has decreased over the last three decades (Arora et al., 2020). Scientists working in universities and research institutes are the primary producers of scientific knowledge. The scientific enterprise that the academic scientists are a part of incentivizes them to share their discoveries and get credit for them while allowing others to use and build upon the knowledge (Merton, 1979). By publishing scientific articles, scientists codify their knowledge and make it available for widespread public use. Therefore, the key challenge for firms is not to produce their own science but to draw upon the external research enterprise for private gain (Cohen and Levinthal, 1990; Fleming and Sorenson, 2004).

In theory, firms should be able to leverage science easily since it is openly available. Yet, firms often fail to capitalize on commercially promising scientific ideas. For instance, less than 5% of scientific papers are directly cited in patents, a measure of commercial use of science (Ahmadpoor and Jones, 2017). The gap in the commercialization of science can be partially attributed to the nature of science; not all fields have immediate or direct commercial applications; however, the gap persists even for commercially relevant scientific discoveries.

Using an *ex-ante* measure of commercial potential, Masclans et al. (2023) report that even for scientific papers that have high commercial potential, more than half are never used in patenting. This gap between scientific discovery and commercial application raises a critical question: Why does science, despite being openly available and commercially relevant, remain under-utilized by firms?

2.2 Scientific Complexity and Importance of Scientific Capacity

Despite the open nature of scientific knowledge, its complexity and reliance on specialized language makes it challenging for firms to leverage scientific advances (Cohen & Levinthal, 1990; Zucker & Darby, 1996). The complexity stems from the cumulative nature of scientific progress, where new scientific advances are contingent on prior knowledge and expertise (Acemoglu et al., 2016; Jones, 2009). The cumulative process of scientific advancement creates a dense network of interconnected ideas and findings, which poses several challenges for firms. Firstly, firms must navigate an ever-expanding body of scientific literature to identify breakthroughs relevant to their domain (Chu and Evans, 2021). Secondly, scientific knowledge is increasingly specialized and distributed across numerous sub-disciplines. This fragmentation leads to: a) difficulty in identifying cross-disciplinary relevance and b) potential for overlooking important advances in adjacent fields, which might lead to more novel and valuable innovations (Fleming, 2001; Shi and Evans, 2023). Thirdly, as scientific fields have evolved, so has the language scientists use to communicate with each other (Baram-Tsabari et al., 2020; Rakedzon et al., 2017). The domain-specificity of scientific texts can create barriers for firms attempting to understand and use scientific knowledge.

Given the complexity of science, firms need capabilities to access, understand, and evaluate scientific literature (Arora & Gambardella, 1994; Cockburn & Henderson, 1998). These scientific capabilities are crucial for identifying promising ideas within growing research bodies, understanding scientific knowledge presented in field-specific terminology, assessing the commercial potential of scientific ideas, and ultimately transforming scientific knowledge into marketable innovations (Rosenberg, 1990; Gittelman & Kogut, 2003). Possession of scientific expertise is a critical factor in a firm's ability to successfully navigate the science-to-market pipeline. Scholars have identified several ways through which firms can build these scientific capabilities. Firstly, conducting internal research and development (R&D) positions firms at the scientific frontier, helps them build expertise in relevant fields, and enhances their ability to recognize and assimilate valuable external scientific knowledge (Gambardella A, 1992). R&D investments also contribute to the development of knowledge-processing routines, facilitating the conceptualization of commercial applications from new scientific discoveries. Second, firms can enhance their capacity to understand and apply new scientific knowledge by strategically hiring researchers with relevant expertise (Rosenkopf and Almeida, 2003). These researchers, particularly those who span scientific and technological domains, play a crucial role in identifying and interpreting external scientific knowledge, as well as translating it into commercial applications (Tushman and Katz, 1980). Third, firms can establish collaborations with academic and research institutions, which serve as conduits for knowledge transfer and facilitate the flow of complex scientific information. These networks provide access to diverse pools of scientific and technological expertise (Powell et al., 1996), exposing firms to cutting-edge research and helping them stay abreast of scientific developments in their field.

While these demand-side, firm-based channels are crucial, however, building and maintaining expertise through these channels entails substantial costs and may not be feasible for many organizations. While internal R&D

activities can aid in building expertise, they require significant financial and human capital investments without guaranteeing direct returns. Expanding scientific expertise across multiple domains through hiring or collaborations increases resource requirements, potentially straining organizational capacities. The benefits of network connections also have limitations, as only a select few firms can be located near particular innovations or have direct ties to their creators, which are crucial for understanding and applying knowledge commercially. These demand-side channels, while vital for innovation, may not be accessible to all firms, especially resource-constrained smaller organizations. Consequently, it is essential to explore alternative channels for firms to identify, understand, and utilize scientific knowledge, particularly those that can provide broader access to scientific knowledge across different fields.

2.3 Communication of Science through Scientific Press

The field of science communication offers a way forward. Scholars in this tradition have long argued that the mere existence of science does not necessarily translate into impact (Burns et al., 2003; Fischhoff and Scheufele, 2013). Conveying the science in an effective manner to the right audiences at the right time is critical to its adoption. Historically, the scientific press, which includes popular science magazines like *The Scientific American*, *Wired*, *Technology Review*; technical magazines, and science sections in newspapers like *New York Times* and *Washington Post*, has been an important mediator of the science public interface (Bucchi, 1998). The scientific press is a part of the scientific ecosystem and is an important channel through which scientific findings reach the public (Goodell, 1977; Nelkin, 1995).

Coverage in the scientific press can amplify the visibility and impact of both scientific ideas and the scientists behind them. For instance, Albert Einstein's transformation from a relatively unknown scientist to a global celebrity occurred largely due to extensive press coverage in the United States and England of the 1919 eclipse expedition, which provided empirical confirmation of his theories (Missner, 1985; Halpern, 2019). Similarly, in the case of the discovery of the double helix structure of DNA by James Watson and Francis Crick, the press picked on the significance of the discovery and presented them using more accessible explanations and speculated on the wider implications of the findings for fighting diseases, understanding heredity, etc. (buc, 2008). More recently, during the COVID-19 pandemic, science journalists worked with scientists to break down complex medical terminology and explain concepts like viral transmission, exponential growth, and herd immunity to the general public, which helped create public awareness and understanding (Leidecker-Sandmann et al., 2022; Mach et al., 2021).

To popularize their research through the scientific press, universities and journals spend significant resources on press information offices (PIOs) that act as liaisons between scientists and science journalists. Various media organizations also employ a whole cadre of scientific journalists who specialize in understanding complex ideas and distilling them for the general public and industry. The US Bureau of Labor Statistics reported over 53,000 Technical Writer positions in 2022, alongside the National Association of Science Writers having more than 2,900 members, indicating that there is a large community of professionals trained in communicating complex scientific information. Studies in science communication have shown that the popularity of scientific ideas in the scientific press is correlated with their technical use, measured by patent citations (Yin et al., 2022). However, the effect of the scientific press on the diffusion of scientific ideas to firms remains an open question.

2.4 Hypotheses

In this paper, I argue that while the scientific press has traditionally been viewed as a means for raising public awareness of science, it may also play a crucial role in the diffusion of scientific knowledge to firms. Evidence suggests that companies are not only paying attention to media in general but are also specifically attuned to the scientific press. The pivotal role of the Whole Earth Catalog in popularizing emerging advances in the personal computing industry during the 1970s and 1980s is well documented (Cadwalladr, 2013). Moreover, media coverage has been shown to influence strategic decisions, such as a firm's choice to enter foreign markets (Kulchina, 2014).

The significance of the press in innovation is demonstrated by its direct use in patenting by firms. For example, over 10,000 patents cite New York Times stories, showing inventors are paying attention to the scientific press to keep up with recent scientific advances. In some instances, press coverage has proven more influential in spurring follow-on firm innovations than the original research paper. For instance, in 2016, a study on diabetic retinopathy by Dr. Michael David Abramoff and colleagues at the University of Iowa challenged existing beliefs about the disease's progression (Sohn et al., 2016). They found that nerve damage precedes blood vessel damage, contrary to previous understanding. This discovery had significant commercial potential in the multi-billion dollar diabetic care market, offering possibilities for improved screening, earlier diagnosis, and more effective treatments. However, the original paper has been cited in only one industry patent. Interestingly, the University of Iowa's press release about the study has been cited in over 19 firm-owned patents, underscoring firms' use of the scientific press for staying informed about scientific advancements and their potential commercial applications.

Furthermore, recent scholarship in science communication has begun to explore the relationship between press and diffusion of scientific knowledge (Fischhoff and Scheufele, 2013; Scheufele, 2013; Fischhoff, 2019b). A few studies have specifically examined the role of media in the diffusion of scientific knowledge within academia and have found a strong correlation between media coverage and the number of citations received by research papers (Phillips et al., 1991; Kiernan, 2003; Anderson et al., 2020; Dumas-Mallet et al., 2020).

Building on this evidence, I argue that the scientific press can be beneficial to firms in identifying and understanding commercially relevant science, especially when firms face higher barriers. Given the complexity of science and scientific language, firms face challenges in identifying and understanding new scientific knowledge. Scientific press can lower some of these barriers and help firms in building on new scientific ideas. I provide a simple theoretical framework that takes into account the different costs faced by firms in accessing and understanding new scientific knowledge and the different ways in which the scientific press can be useful to firms.

2.4.1 Theoretical Framework

Consider a scenario in which the scientific community generates N new scientific ideas, denoted as $(a_1, a_2, \ldots, a_N)$. For firms to build on these ideas, they must first become aware of them. Secondly, although these scientific ideas are available, they are not "costless" because firms require specific capabilities to understand and assimilate them (Rosenberg 1990). Thirdly, given inventors and firms have limited cognitive resources and cannot explore all new scientific ideas, firms need heuristics to identify which scientific ideas are commercially promising and to determine the best ideas to pursue.

For a focal firm, let's assume there is a fixed cost λ_i to understand and evaluate a scientific idea. Each firm has an internal measure U_i of the commercialization potential of an idea and a cost C_i for commercializing the idea. Moreover, each firm has a resource constraint θ_i for the ideas it can evaluate and a budget constraint ϕ_i for commercialization activities.

In a situation where the firm is aware of all the scientific ideas N and does not have to pay any costs for understanding and evaluating new knowledge ($\lambda_i = 0$), the firm will choose the ideas with the highest commercial potential, subject to its budget constraints in commercializing those ideas.

$$\text{Choose } j \in J \text{ such that } U_i(a_j) > U_i(a_k) \text{ for all } k \in J, k \neq j \text{ and } \sum_{j \in J} C_i(a_j) \leq \phi_i$$

However, if the firm has to pay a cost λ_i in understanding and evaluating the scientific ideas, then it can only explore a subset M_i (consisting of m_i ideas) out of N due to resource constraints.

$$m_i = \left\lfloor \frac{\theta_i}{\lambda_i} \right\rfloor$$

The set of ideas that a firm can explore is now restricted to M_i, and it will choose the ideas with the highest commercialization potential from M_i.

$$\text{Choose } j \in M_i \text{ such that } U_i(a_j) > U_i(a_k) \text{ for all } k \in M_i, k \neq j \text{ and } \sum_{j \in M_i} C_i(a_j) \leq \phi_i$$

Consequently, firms are likely to leave potentially commercializable ideas on the table, as they can only explore m_i ideas out of N. Similarly, in a situation where the firm is not aware of all scientific ideas N, it will only explore a subset L_i of ideas and may miss out on other commercially relevant scientific ideas. If we were to assume heterogeneity in costs of understanding and evaluating ideas, (λ_{a1i},λ_{a2i},..), firms are still subject to the resource constraint and will explore ideas till they hit the constraint.

Implications: Given the resource constraints of firms, any activity that lowers λ_i (or λ_{aki}) for a firm can lead to increased use of new scientific ideas, as firms can understand and evaluate more scientific ideas while still maintaining their resource constraints.

I argue that the scientific press can help firms by both expanding L_i, the set of ideas that a firm is aware of, and M_i, the set of ideas that a firm tries to understand and evaluate. Firstly, press coverage can highlight significant scientific advancements that firms might otherwise overlook. Given the vast volume of published research – over 70 million papers were published between 2010 and 2020 (Masclans et al., 2023) – it is increasingly challenging for any organization to stay informed about all relevant developments. This growth in science can make it challenging for inventors and firms to keep up with recent advances. The scientific press can help firms identify promising research. Science journalists and communicators often track developments across disciplines, identifying breakthroughs and emerging trends that might be relevant to various industries. This curation can be valuable for firms seeking to stay informed about new scientific discoveries.

Secondly, the scientific press can help firms lower the costs of understanding and evaluating new scientific ideas. Press coverage can serve as an initial filter, helping firms decide which original papers are worth investing time to read in full. It makes complex information more accessible, lowering the costs of understanding and evaluating new scientific ideas. Additionally, scientific press often discusses potential applications or implications of research, which can help firms better understand how new knowledge might be relevant to their work.

In summary, the scientific press can help firms identify and understand new scientific discoveries by serving as an intermediary between academic science and commercial innovation. It curates important new findings from the growing scientific literature, contextualizes discoveries within the broader scientific landscape, and communicates science using an accessible language. Communication of science for the general audience in the scientific press can help firms in building on new scientific advances.

H1: Firms are much more likely to draw on scientific knowledge that has been communicated to a more general audience.

While the scientific press increases commercialization by highlighting new scientific developments, validating emerging ideas, and simplifying complex information, its most distinctive feature is scientific translation—the communication of scientific ideas using simple, non-technical language. The use of specialized language in academic research presents a major barrier that limits the understanding of science by non-experts, including engineers in firms (Allen, 1984). I argue that scientific translation serves as a crucial mechanism in bridging the gap between academic research and industrial application.

A fundamental challenge in the diffusion of scientific knowledge to industry lies in the misalignment of goals between academia and the private sector, which creates communication barriers. Scientists in academia operate under a distinct set of motivations, primarily driven by the pursuit of knowledge and recognition within their scientific communities (Merton, 1979; Partha and David, 1994; Stephan, 1996). Scientists primarily write for an academic audience, often peers within the same subfield. Scientific texts rely on specialized language as it facilitates evaluation and discourse within the field (Myers, 1985; Cheng et al., 2023). The use of specialized language helps scientists draw links to existing scientific concepts and situate their ideas within the broader inquiries of their field, making it easier for evaluators to understand and assess the work's novelty and validity (Cheng et al., 2023; Denrell and Kovács, 2020)

In contrast to academia, industry's use of scientific knowledge is predominantly guided by commercial objectives, seeking insights that can be directly applied to commercial products (Allen, 1984; Rosenberg and Nelson, 1994; Sauermann and Stephan, 2013). While specialized language facilitates communication within scientific fields, it significantly hinders the diffusion of ideas beyond these boundaries (Lucy et al., 2023). Recent studies have noted an increasing trend in the use of specialized words, or jargon, in scientific papers. The increased use of jargon not only limits readability (Dumas-Mallet et al., 2020; Plavén-Sigray et al., 2017) but can also reduce attention and engagement among non-experts (Shulman et al., 2024). As a result, even though inventors in firms recognize the importance of scientific literature, they are less likely to utilize it, as they find formal scientific literature incomprehensible. (Allen, 1984; Tushman and Katz, 1980).

The use of specialized language increases the cost of understanding and evaluating new scientific knowledge

(λ_{aki}) (McMahon and Naylor, 2024; Shulman et al., 2024). Consequently, firms face a dilemma: they must either invest resources to understand scientific ideas communicated using specialized language, potentially at the expense of pursuing other opportunities, or opt for more easily understandable alternatives that may have lower commercialization potential. Either choice alters the set of ideas (M_i) that a firm evaluates and considers for commercialization.

Firms and inventors can lower the costs of understanding and evaluating new scientific idea (λ_{aki}) by turning to scientific press which provides succinct summaries of new discoveries in a language that is easier to understand (Meredith, 2021). Magazines like Scientific American or trade journals translate scientific knowledge by communicating it in a simpler, non-technical language. These popular science communication outlets serve as the "simplified sources" of new scientific knowledge that are easier to understand (Allen, 1984). Scientific translation can make it easier for firms to understand new scientific discoveries, especially in domains where they lack prior scientific expertise. By presenting scientific advancements in accessible language, the scientific press reduces the cost of understanding new scientific ideas ($\lambda_{a_k i}$), which can lead to an increase in commercial use. I posit that costs of understanding are higher for papers that use more specialized words, making scientific translation particularly useful to firms in these cases.

H2: The benefits of scientific translation are greater for scientific knowledge that employs more specialized language.

While scientific translation reduces the cost of understanding new knowledge, it is unclear if it acts as a substitute or a compliment to firm existing scientific capabilities. Scientific translations may act as a substitute for scientific expertise by providing an alternative, low-cost means of understanding science, potentially leveling the playing field for firms lacking extensive in-house scientific expertise. This substitution effect could democratize access to cutting-edge research, allowing a broader range of firms to participate in science-driven innovation (Arora and Gambardella, 1994; Arora et al., 2022). However, it's important to note that while translation can help firms in understanding new scientific discoveries, it does not necessarily confer the ability to meaningfully build upon or apply this knowledge. The capacity to leverage scientific insights for innovation requires an understanding of scientific methodologies and engagement with science (Cohen and Levinthal, 1994; Cockburn and Henderson, 1998). Firms without this underlying expertise may find themselves unable to fully capitalize on the translated knowledge.

For instance, for a scientific idea a_1, two firms i_1 and i_2, will face different costs in understanding and evaluating the idea, λ_{i_1} and λ_{i_2} respectively. Scientific translation can help in lowering these costs. The firms might come to similar conclusions about the commercial potential of the idea; however, they will face different costs, $C_{i_1}(a_1)$ and $C_{i_2}(a_1)$, in commercializing the idea. These costs are shaped by prior scientific expertise and engagement, among other factors. Importantly, for a firm without any prior scientific expertise, the cost $C_i(a_1)$ can potentially exceed its budget constraint. This means that even if such a firm realizes the scientific potential of an idea through scientific translation, it may still be unable to build upon that idea due to the lack of necessary capabilities.

Firms with prior expertise in science face lower costs in both understanding and commercializing new scientific ideas. Their prior expertise and engagement allow them to speak the language of science. Consequently, the marginal benefit of scientific translations will be low for such firms.

Scientific translation presents a paradox in its value to different firms. Firms with strong scientific capabilities will find little benefit from scientific translations, as their existing expertise allows them to engage directly with complex scientific texts. Conversely, firms lacking scientific capabilities struggle to derive value from translated science, as they don't possess the foundational knowledge to build upon or apply the simplified information effectively. This creates a conundrum where the firms that have the capability to build on science don't require scientific translations, while those that might need it are ill-equipped to build on it without incurring high costs.

However, this view overlooks a crucial aspect of modern scientific research: the rapid growth and increasing specialization of scientific knowledge, leading to highly focused sub-fields (Jones, 2009). This specialization results in knowledge fragmentation, creating barriers to information flow between different sub-fields. Consequently, even firms with strong scientific capabilities in certain areas may find themselves at a loss when confronted with scientific developments from distant or unfamiliar fields. While firms may build expertise in a few sub-fields, doing so across all relevant scientific domains is impractical, even for large, resource-rich organizations. Firms often struggle to understand and evaluate new scientific knowledge from distant fields (Boudreau et al., 2016), yet insights from these areas can frequently lead to novel and valuable innovations (Uzzi et al., 2013; Kaplan and Vakili, 2015).

Scientific translation through the press can bridge this gap, helping firms with expertise in one field understand new developments in other related fields (Habermas, 1971). Scientific translations reduce the cost of understanding and evaluating scientific insights from fields in which the firm lacks prior expertise. By facilitating cross-field knowledge transfer, scientific translations allow scientifically capable firms to expand their expertise across related but unfamiliar scientific territories. Thus, rather than being superfluous for scientifically adept firms, translations serve as a vital tool for extending their reach into previously unexplored domains.

In conclusion, I argue that scientific translation will be useful to firms for distant search. In scientific areas where the firm has expertise, the marginal benefit of scientific translations will be lower, as the firm has prior capabilities and can engage directly with the primary scientific literature. However, scientific translations will be especially useful in scientific areas where the firm does not have prior expertise. By presenting scientific knowledge using a simple language, scientific press can make it easier for experts to understand ideas from from fields in which do not have prior expertise. Consequently, scientific translations will act as a substitute for firms with prior scientific expertise in areas of science where that are outside their core areas of expertise.

H3a: The benefits of scientific translation are greater for firms with prior scientific expertise.

H3b: The benefits of scientific translation are greater in scientific fields in which the focal firm does not have strong expertise.

3 Empirical Setting

The ideas I have presented are best explored empirically in a setting where firms heavily rely on scientific research and innovation is closely tied to scientific advances. Biomedical sciences provide an ideal context for this investigation. The development of new drugs, medical devices, and therapies is directly dependent on the latest advancements in research. The field bridges multiple disciplines, including biology, chemistry, and medicine, creating a complex ecosystem where scientific knowledge from various sources is combined

to drive innovation. Firms in the biomedical sector must stay informed about developments in their specific area of expertise while also integrating insights from related fields, making it a rich context for studying how the complexity of science and its communication impacts its commercial use. Additionally, the biomedical industry places a strong emphasis on intellectual property protection through patents, which not only safeguard innovations but also provide a tangible record of how scientific research is translated into commercial products, allowing me to trace the direct influence of academic research on innovation.

In order to study the relationship between scientific press and the commercial diffusion of science, I need comprehensive data on science-related press coverage. However, obtaining this data is challenging due to the vast and diverse nature of the scientific press, which spans a range of media outlets, including prominent national newspapers like the New York Times and Washington Post, specialized magazines such as Wired and Scientific American, numerous trade journals, and digital platforms like The Conversation, MedicalXpress, Science Daily, and Quanta. The emergence of large-scale datasets such as AltMetrics, PlumX, and CrossRef, which link scientific articles to their mentions across both traditional and social media, has opened up new avenues for studying public engagement with science (Yin et al., 2022). However, these datasets have a few limitations. They lack historical coverage—AltMetrics, for instance, only provides information dating back to 2011. Moreover, even for more recent periods, the completeness of coverage offered by these datasets remains uncertain (Ortega, 2018; Wang and Yu, 2021).

While the press ecosystem seems vast, much of the science coverage relies on official press releases issued by university offices. Science journalists face numerous challenges in gathering and reporting news about scientific developments. The sheer volume of research being published across various fields makes it nearly impossible to stay on top of all new findings. In many cases, the journalists have some familiarity with the science but lack the expertise to evaluate it. Scientific papers are usually written in dense, technical language intended for an audience of experts, making it challenging for journalists without a deep background in that specific field to grasp the nuances. The news cycle is fast, and journalists often do not have time to engage deeply with the scientific text. Furthermore, gaining direct access to researchers for interviews can be difficult as scientists may be hesitant to engage with the media. Additionally, many news outlets have closed local bureaus and science desks in the last couple of decades, eliminating specialized science journalists who once maintained close ties with research institutions. Consequently, science coverage increasingly falls to generalist journalists or freelancers who lack both specialized expertise and time to thoroughly understand complex scientific subjects.

In this environment, press releases have become an indispensable tool. They provide a summary of the research in more accessible language, highlighting key findings and placing the work within a broader context that is relevant to the public. This makes it easier for journalists to quickly understand the significance of the research without needing to wade through dense technical jargon. Press releases also often include quotes from the researchers involved, which can be directly incorporated into news stories, saving time and providing authoritative voices on the subject. Moreover, press releases help journalists by framing the research in a way that emphasizes its newsworthiness. They often draw attention to aspects of the study that have broader implications, such as potential applications, societal impacts, or surprising results, which can be compelling for a general audience.

3.1 EurekAlert

The process of producing and disseminating press releases in the scientific community was informal and disorganized till the mid-90s. Press officers at universities and journals created press releases that were typically distributed through a mix of faxes, emails, and traditional mail (Marshall, 1998). Journalists interested in covering a particular study had to request the full text of the research paper. All the information was embargoed until the day of publication of the focal paper to ensure that press coverage coincided with or followed the official release of the study.

An organizational innovation led by the American Association for the Advancement of Science (AAAS) significantly transformed science communication in 1996 with the launch of EurekAlert, a platform that quickly became the central channel for journalists to access press releases from official sources about upcoming scientific articles. This platform allowed institutions and academic journals to post press releases up to two weeks before a paper's publication, and many journals also provided access to the full forthcoming papers through the platform. Journalists who subscribed to EurekAlert could view these official press releases and papers, enabling them to prepare their coverage in advance and ensuring that news stories were ready to go as soon as the embargo was lifted. EurekAlert streamlined the communication process between academic institutions and the media, making it significantly easier for journalists to find and access new scientific insights. By 2003, the platform had grown substantially, with over 2,000 press officers from more than 1,000 institutions and over 4,400 journalists utilizing the service, which was receiving 400,000 visits each month (Sirica, 2003). Over the past two decades, EurekAlert has continued to expand, posting over 35,000 press releases in 2020.

By focusing on EurekAlert, I can get a complete picture of the supply of press releases that form the basis for most media stories about scientific research. Moreover, as I report in the results, a press release on EurekAlert is strongly correlated with the overall level of media coverage. This finding is in line with work that found that being featured on EurekAlert, and Science Daily (a press release aggregator) is the most important feature for predicting media coverage of scientific articles (MacLaughlin et al., 2018).

3.2 Data Sources

Three key data are needed to study the relationship between press coverage and the use of scientific knowledge in firms: (i) publication records, (ii) press coverage of scientific papers, and (iii) commercial use of scientific papers. The primary data sources I use are summarized below:

Publication Data: I use OpenAlex, an openly available bibliometric database, for publication records. The dataset provides information about scientific papers, including their titles, abstracts, names, and affiliations of authors, the name of the journal, the scientific field, and the date of publication.

Press Release: For the press releases of scientific papers, as mentioned earlier, I rely on EurekAlert. Over 68,000 papers in the sample received a press release.

Commercial Use of Science: I rely on the *Reliance on Science* dataset (Marx and Fuegi, 2022) that matches scientific papers to patent citations. I apply two crucial filters to the data: first, I focus exclusively on patents owned by firms, excluding those held by individuals or non-commercial entities; second, I remove all self-citations to eliminate potential bias from inventors citing their own research. After applying these filters, the

resulting dataset contains over 277,000 firm-owned patents that cite at least one scientific paper in the sample.

Scientific Expertise: To identify firm expertise, I utilize the PQR dataset (Scharfmann et al., 2024), which catalogs scientist-inventors (SIs) - individuals who have both patented inventions and published scientific papers. For each SI, I compile a comprehensive list of their patents and scientific publications. I then match these SIs to their respective firms using patent assignee data. This approach allows me to map out each firm's scientific expertise across various fields. Specifically, I determine a firm's expertise in a particular scientific area based on whether any of its SI employees have published papers in that area. This method provides a granular measure of a firm's scientific capabilities based on the research output of scientist-inventors it employs.

Commercial Potential: Masclans et al. (2023) use a machine learning-based approach to provide ex-ante measures of the commercial and scientific potential of scientific papers. I use this data to analyze PIO selection. I can match 58% of the papers in my sample to this dataset.

Jargon Words: Lastly, to analyze the complexity and specialization of scientific language, I use data from Lucy et al. (2023). This dataset identifies "jargon words" - terms that are either unique to specific scientific subfields or carry distinct meanings within those areas. The researchers constructed this dataset using the Microsoft Academic Graph (MAG), which uses the same subfield classification system as OpenAlex. This alignment facilitates easy integration with my existing data.

3.3 Matching EurekAlert Press Releases to Papers

While EurekAlert press release data is publicly available, it needs to be matched to publication data. To achieve this, I collected all press releases posted on the platform between 1996 and 2020. The dataset includes the text of each press release along with metadata such as the name of the posting institution, contact details of the press information officer who created the post, the date of publication, and relevant keywords. To match these press releases with the corresponding scientific publications, I first extract the names of individuals or organizations mentioned in each press release. I then compare these extracted names against the set of all papers published around the time the press release was posted. To make the matching process manageable, I restrict the publication data to papers authored by researchers at the top 100 U.S. universities based on U.S. News rankings. Additionally, since most press releases are published close to the time of the paper's release, I focus on finding matches within a 45-day window around the publication date.

In recent years, EurekAlert has started including DOI (Digital Object Identifiers) in press releases, which simplifies the matching process. By comparing posts with DOIs to those matched using name-based methods, I found that over 80% of the posts were correctly matched, validating the effectiveness of the name-based approach.

3.4 Descriptive Statistics

By combining data from OpenAlex, EurekAlert, and Reliance on Science, I am able to construct data on publication records from the top 100 US universities, along with information on whether or not the paper received a press release and link papers to patents that cite them. Given its relevance to commercial innovation, I restrict the sample to papers in Biomedical science (Mezzanotti and Simcoe, Mezzanotti and Simcoe). I use OpenAlex field classifications to identify papers in Biology, Chemistry, and Medicine. The final sample consists

of 2,687,312 papers, with nearly half of these (50%) in Medicine. Biology and Chemistry papers make up 28% and 22% of the sample, respectively. The summary statistics, as outlined in Table 1, show that approximately 2.9% of the papers in the sample received a press release, and about 8.0% received at least one patent citation. The proportion of papers that received a press release is 4.4% for Biology, 2.6% for Medicine, and 1.6% for Chemistry. Regarding patent citations, Biology and Chemistry papers were more frequently cited, with 12.0% and 11.4% cited by at least one patent, respectively, compared to only 4.3% of Medicine papers receiving patent citations. Papers that receive a press release are, on average, 2.4 times more likely to be cited by a patent and receive over three times more patent citations.

4 Research design

While papers that receive press releases are more likely to be cited by the patents, other common factors, like the quality of the publication, could drive the relationship. To identify the causal impact of media coverage on patent citations, I need exogenous drivers of media coverage that are independent of the quality of any given article. In this section, I will introduce the baseline model and provide details on the variables it includes. I will then discuss the potential threats to causal inference and propose an instrumental variables approach to address these challenges.

In order to study the effect of media coverage on patent citations, we can estimate the following model:
For paper i in field f, published in academic journal j, at time t.

$$Patent\ Citations_i = \beta \times Press\ Release_i + X_i + \rho_{ft} + \gamma_{jt} + \eta_t + \varepsilon_{ifjt} \tag{1}$$

where $Patent\ Citations_i$ is the number of patent citations received by paper i from patents owned by firms. $Press\ Release_i$ is a dummy variable indicating if the paper received a press release or not. X_i are paper characteristics like the number of authors, number of unique affiliations, etc. The coefficient β, if well identified, would be interpreted as the number of additional patent citations that a paper receives due to coverage in a press release.

In estimating the model, we should account for the fact that there may be changes across time, journals, and fields that may simultaneously correlate with press release coverage and citations. For example, new technological opportunities in a field could lead to more papers, more press release postings, and more patents in that field. To account for such possibilities, I include field-time fixed effects at the field-year level (ρ_{ft}). Similarly, some academic journals, for e.g., those publishing higher quality research, may be more likely to be read by inventors at firms and also more likely to receive press coverage. I include journal-year fixed effects (γ_{jt}) to account for such possibilities. Additionally, more funding over time for science can increase the quality of research and the likelihood of press coverage. I control for that possibility, including time-fixed effects at year-month level (η_t).

There is one remaining characteristic of papers that may increase both the likelihood that an academic article receives a press release and the number of citations that the paper receives: the quality of the paper. In other words, the PIOs may not be randomly selecting papers that receive a press release but rather selecting a specific set of high-quality articles, leading to sample selection bias. As a consequence, if we were to interpret β in the current model, we may wrongly interpret that a paper receives higher citations in the future as the effect of a press release when it is actually due to the underlying higher quality of the paper. If the PIOs favor high-quality

papers for press releases, then the simple estimation would overestimate the effect that a press release has on subsequent patent citations. I approach this concern in two complementary ways: first, by including article-level controls such as the number of authors and amount of different institutional affiliations in the article (included in X_i). By doing so, I control for the observables that the PIO might take into consideration when deciding between papers.

4.1 Instrument Variable: Congestion in Press Information Offices

Second, I implement an instrumental variables strategy. For a valid instrument, I need a variable that is relevant and satisfies the exogeneity condition; that is, it affects a paper's likelihood of receiving a press release without directly influencing its citation count, except through the channel of the press release itself. I argue the congestion at the press office at a university, which can be measured as the number of papers in the fields other than the focal papers field that are published in the same week as the focal paper, can be used as an instrument. The operational logic of this approach is informed by the practices on EurekAlert: press offices can post releases up to two weeks before a paper's publication, although most releases appear about a week in advance. This timing mechanism introduces variability in the number of papers eligible for press coverage in any given week. Different publication schedules across fields and journals result in fluctuations in the weekly output of published papers at a university. Consequently, in weeks with a higher volume of publications, the odds of any specific paper being selected for a press release diminish — not due to its quality but due to the logistical 'congestion' experienced by the PIO.

Formally, the first stage of the instrumental variables estimation is as follows:

For paper i in field f published by authors at university u in academic journal j, at time t.

$$Press\ Release_{iu} = \alpha \times Total\ Weekly\ Articles_{-f,uw} + \lambda_{ft} + \sigma_{jt} + \tau_t + X_i + \xi_{ijft} \tag{2}$$

Where $Press\ Release_{iu}$ is a binary variable indicating whether the paper received a press release from university u's press office or not. $Total\ Weekly\ Articles_{-f,uw}$ is the number of academic articles published by scientists at university u in the week w in fields other than focal paper's field f. This instrument is a proxy for the level of congestion that an academic article, i, faced at its university's press office. λ_{ft} is field-year fixed effects, σ_{jt} is journal-year fixed effect, and τ_t are time fixed effect (year-month).

4.1.1 Illustration of the empirical design

Figure 2 provides an illustration of the design for a set of papers published by Hongje Dai and co-authors from Stanford University, focused on carbon nanomaterials. In 2005, they published two papers in the Proceedings of the National Academy of Sciences (PNAS). The first paper, released on August 8, 2005, coincided with a week of low congestion at Stanford's press office, and the paper received a press release from the Stanford press office. This paper has subsequently been cited by over 440 patents from 46 different firms. In contrast, the second paper was published on November 1, 2005, during a busier week for the press office, and did not receive a press release. This paper received significantly fewer citations, with just 15 patent citations from 9 firms. The timing of these publications relative to the press office's congestion illustrates the design: had the second paper

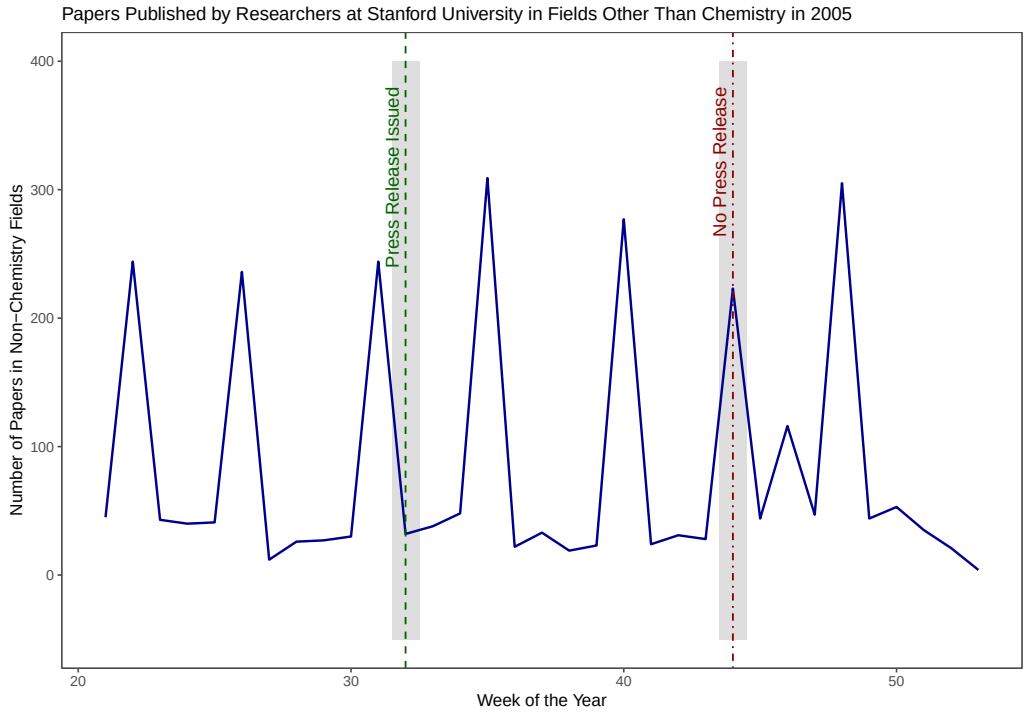


Figure 1: The plot shows the number of papers published each week by researchers affiliated with Stanford University across all fields except Chemistry in 2005.

been published a week earlier during a less congested period, it might have received a press release, potentially increasing its exposure and citation count. Conversely, had the first paper been published a week earlier, during a more congested period, it might not have received a press release, possibly resulting in fewer citations. The IV approach leverages the randomness in the timing of congestion to identify the effect of press releases.

4.1.2 Papers with multiple university affiliations

Many papers in the sample have authors from multiple universities. While EurekAlert allows only one press release per publication, the press release could have been posted by the press office of any one of the universities. To deal with such a structure, I aggregate treatment (receiving a press release) at the paper level.

$$PressRelease_i = \max_{\forall u}(PressRelease_{iu}) \quad for\ u = 1,2,\ldots,n \tag{3}$$

$PressRelease_i$ takes the value 1 if the press office at any one of the universities posted a press release.

I similarly combine university-level shocks $TotalPapers_{-f,uw}$ to construct a measure of congestion faced by the paper across all the relevant press offices. The intuition behind the transformation is that the press release will most likely be posted by the least congested press office. The resultant paper-level instrument, *Congestion Index Raw*, reflects this aggregated measure of PIO activity.

$$Congestion\ Index\ Raw_{ifw} = \min_{\forall k}(TotalPapers_{-f,u_kw}) \quad for\ k = 1,2,\ldots,n \tag{4}$$

The measure, however, does not account for variations in the size of different universities and their average volume of published papers. To address this, I refine the measure by normalizing the $TotalPapers_{-f,uw}$ for each university on a yearly basis. The normalization adjusts for each university's publication activity, ensuring that the Congestion Index reflects a comparable measure of PIO workload across different universities.

$$Congestion\ Index_{ifw} = \min_{\forall k}(\widehat{TotalPapers}_{-f,u_kw}) \tag{5}$$

where $\widehat{TotalPapers}_{-f,uw}$ is computed by normalizing value of $TotalPapers_{-f,uw}$ within a university-year.

I find that congestion is negatively related to press release coverage. Papers published in weeks of higher congestion are less likely to receive a press release. Figure 2 shows the negative relationship between *Congestion Index* and the likelihood of receiving a press release.

4.1.3 Threats to Identification

The exclusion restriction requires that the instrument (press office congestion) affects the dependent variable (patent citations) only through its effect on the independent variable of interest (press release issuance). If congestion indirectly affects patent citations through other channels, the exclusion restriction is violated, compromising the causal interpretation of the IV estimates. A few scenarios could lead to such violations in this setting.

Overall congestion in scientific publication: The instrumental variable measures the congestion at university press offices due to papers in fields other than the focal paper's field. While different fields operate on different timelines, the overall volume and quality of scientific publications might still exhibit systematic correlations. For instance, if periods of low congestion across different fields tend to align with the publication of high-impact or high-quality papers, this could imply that the IV—congestion—is indirectly related to the quality of these papers. As a result, any observed increase in patent citations might reflect the inherent quality of the papers more than the effect of receiving a press release.

Strategic timing by journals: Journals might adapt their publication schedules in response to congestion levels, choosing to expedite or delay the release of high-quality papers to match less congested times. This would confound the relationship between press releases and citations, as the variation in citation rates could be attributed incorrectly to reduced congestion (and thus supposedly more frequent press releases) rather than the strategic timing of their publication.

Selection by university press offices: Any differences in the selection of papers by PIO during less congested weeks can change the interpretation of the results. For instance, PIOs have fewer papers during the less congested weeks and might be better able to identify high-quality papers during the less congested weeks and feature them. However, in more congested weeks, they might not be able to pick high-quality papers, leading to differences in the quality of papers covered during congested and less congested that are also correlated with the IV.

Variation in press release quality: The instrument captures quantity (congestion) but not quality of press office work. There might be periods where press offices are less congested but more effective, or vice versa, which could affect both the likelihood of press releases and the paper's impact.

While the exclusion restriction in an instrumental variable analysis is not directly testable, I provide suggestive evidence to mitigate concerns about these potential violations.

5 Results

5.1 OLS Results

Table 2 shows the OLS estimates for the effect of press releases on the likelihood of patents being cited. Model (1) shows the presence of a press release is associated with a 12.2 percentage point increase in the probability of a patent receiving at least one citation ($p < 0.01$). This coefficient suggests that receiving a press release increases the likelihood of citation by 1.5 times. Model (2) introduces control variables, specifically the number of co-authors of a paper and their affiliations. Including these controls slightly diminishes the effect of press releases on patent citations to 9.92 percentage points ($p < 0.01$). This suggests that while the number of co-authors is positively correlated with citation rates, the influence of press releases still holds a strong independent effect. Each additional author increases the likelihood of citation by approximately 0.007 percentage points ($p < 0.01$).

In Models (3) and (4), fixed effects for field-year and journal-year are respectively incorporated. The inclusion of these fixed effects aims to control for field-specific and journal-specific trends in citation practices. The coefficients for press releases slightly decrease in these models to 9.69 percentage points in Model (3) and 5.06 percentage points in Model (4) (both $p < 0.01$), indicating that part of the impact of press releases can be attributed to field-related and journal-related factors. Models (5) and (6) show results for different measures of the outcome variable—total patent citations and the logarithm of total citations plus one, respectively. In Model (5), the effect of a press release on the total number of citations is 0.697 ($p < 0.01$).

The results in Table 2 indicate that papers receiving press releases are more likely to be used in commercial applications. However, this relationship could be due to selection: high-quality papers are more likely to both receive press coverage and be cited in patents.

5.2 PIO Selection

The results in Table 2 indicate that papers receiving press releases are more likely to have commercial applications. However, this correlation may be due to selection bias: high-quality papers might be more likely to both receive press coverage and be cited in patents. To address this, I differentiate between papers' scientific and commercial potential using data from Masclans et al. (2023). I find that press offices are more likely to select papers with high scientific potential, but surprisingly, they are less likely to choose papers with high commercial potential. In fact, after controlling for journal effects, the relationship between commercial potential and the likelihood of receiving a press release becomes negative.

Table 3 presents the relationship between the likelihood of a paper receiving a press release and its commercial and scientific potential. In Model (1), there is a significant positive association between commercial potential and the issuance of a press release, with a coefficient of 0.0172 ($p < 0.01$). This suggests that papers that are commercially relevant are more likely to be selected for press releases. However, in Model (2), after accounting for journal fixed effects, the relationship between commercial potential and press releases becomes negative ($\text{coefficient} = -0.0031, p < 0.01$). This shift indicates that PIO selection is influenced by journal prestige:

insofar as commercially relevant papers are published in high-ranking journals, PIOs select them. However, they might prioritize papers using different criteria to identify important papers when selecting within a journal.

In Model (4), instead of commercial potential, I focus on the scientific potential, which shows a strong positive effect on the likelihood of issuing a press release $(\text{coefficient} = 0.0564, p < 0.01)$. The addition of journal fixed effects in Model (5) reduces the coefficient to half. However, the relationship between scientific potential and the likelihood of receiving a press release is still positive.

Finally, Model (7) combines the effects of both commercial and scientific potentials along with fixed effects for the Journal-Year, Year-Month, and Field-Year. It shows that scientific potential has a positive correlation with press release likelihood (coefficient = 0.0417, $p < 0.01$), whereas commercial potential exhibits a significant negative association (coefficient = -0.0106, $p < 0.01$).

These findings suggest that PIOs prioritize papers with high scientific merit for promotion while being less likely to select those with higher commercial potential. Under such selection, the OLS estimates will be downward biased. This bias arises because the selection process introduces a negative correlation between press release issuance and the unobserved factors that contribute to commercial potential. Specifically, papers that receive press releases tend to have higher scientific potential but lower commercial potential, all else equal. However, papers with high commercial potential that do not receive press releases may still be cited in patents due to their inherent market relevance. Consequently, the OLS estimates likely underestimate the true causal effect of press releases on commercial applications. By failing to account for this negative selection on commercial potential, the OLS approach may understate the impact of press coverage on a paper's likelihood of being cited in patents.

5.3 First Stage: Congestion at Press Office

To address endogeneity concerns, I use an instrumental variable approach. The instrument, *Congestion Index*, exploits the the weekly congestion at the university press office due to higher volumes of papers published by researchers in fields other than the focal papers field to causally identify the effect of press release coverage on commercial diffusion of science. For *Congestion Index* to be a valid instrument, it should be relevant; that is, it should affect the likelihood of a paper receiving a press release.

The results in table 4 show a consistent and significant negative relationship between the weekly Congestion Index at the university press offices and the likelihood of a paper receiving a press release during that week. Model (1) indicates that an increase in the Congestion Index is associated with a 17% reduction in the probability of a press release (coefficient = -0.0045, $p < 0.01$), controlling for year-month fixed effects. As additional controls for the number of co-authors and their affiliations are introduced in Model (2), the magnitude of the congestion effect diminishes slightly (coefficient = -0.0033, $p < 0.01$). The coefficients suggest that papers with more co-authors are more likely to receive press releases. However, the likelihood of press release issuance declines with an increase in the institutional diversity of the co-authors.

The introduction of field-year and journal-year fixed effects in Models (3) and (4) further adjusts the estimates, yielding coefficients of -0.0047 and -0.0016, respectively. The coefficient in Model (4) indicates that a one standard deviation increase in the Congestion Index is linked with a 6% decrease in the likelihood of a paper receiving a press release. Figure 2 shows the plots of the change in the likelihood of a paper receiving a press release as congestion increases. Panel (a) plots the raw data and shows a strong negative relationship. In panel

(b), I graph the binscatter plot of residuals after adding controls and fixed effects, which shows a strong negative relationship.

5.3.1 Exclusion Restriction: Variation in Quality

The validity of *Congestion Index* as an instrumental variable hinges on two key conditions: relevance and exclusion restriction. While the first-stage results in Table 4 demonstrate relevance, the exclusion restriction requires that the instrument affects the outcome (patent citations) solely through its impact on press release issuance. The exclusion restriction would be violated if the *Congestion Index* directly influenced patent citations or operated through channels other than press releases. A specific concern is the potential correlation between the instrument and paper quality or commercial potential. For example, if papers with higher commercial potential were systematically published in less congested weeks, the instrument would be correlated with quality, potentially biasing the instrumental variable estimates.

Although the exclusion restriction is not directly testable, I provide suggestive evidence to rule out any correlation between the *Congestion Index* and paper quality. Using data from Masclans et al. (2023), I measure both the scientific and commercial potential of papers. Figure 4 presents binscatter plots illustrating the relationship between these potentials and the instrument. Panel (a) demonstrates no discernible relationship between the *Congestion* Index and commercial potential (coefficient =0.0003, $p > 0.1$). Papers with high commercial potential are equally likely to be published in weeks with low or high congestion.

Panel (b) reveals a slight negative relationship between scientific potential and the instrument (coefficient = -0.0035, $p < 0.5$), indicating that papers with high scientific potential are somewhat more likely to be published during less congested weeks. However, the magnitude of this relationship is small: a one standard deviation change in congestion is associated with only a 0.05% change in scientific potential.

The results collectively strengthen the case for the *Congestion Index* being unrelated to the commercial potential of papers and rule out violations due to any systematic correlation between congestion and publication quality.

5.4 Causal Effect of Media Coverage on Commercial Diffusion

I test Hypothesis 1, which states that firms are more likely to use scientific knowledge that has been translated for a general audience. If the hypothesis is true, then the effect of a press release on patent citations should be positive. Table 5 presents the results of estimating Equation 1 using the Two-Stage Least Squares (2SLS) method across different transformations of the outcome variables. I show the results for *Patent Citation (0/1)*, a binary indicator of whether the paper received any citation from a firm-owned patent; *Patent Citations*, the count of citations from firm-owned patents; and *Log(Patent Cites+1)*, a transformation addressing the skewed distribution of patent citations.

Model (1) displays the estimates for the effect of *Press Release* on *Patent Citations (0/1)*, which is a dummy variable indicating whether the article received at least one citation from a firm-owned patent. This model controls for year-month fixed effects, yielding a statistically significant coefficient of 0.402 (p¡0.01). Model 2 introduces additional controls for the number of authors (N. Authors) and affiliations (N. Affiliations), the coefficients of 'Press Release' remain significant but slightly decrease to 0.396. In Model 3, I add Field-Year fixed effects, which substantially increase the coefficient to 0.924. The shift in the coefficient is suggestive of

field-level heterogeneity in treatment effect.

Model (4) includes Journal-Year fixed effects. The F-statistic for the first stage is 141, well above conventional thresholds for weak instruments. The coefficient on press releases is 0.839. This can be interpreted as an 83.9 percentage point increase in the likelihood that a paper will be cited by at least one firm-owned patent. To put this effect in perspective, it represents a 10.5-fold increase in the probability of commercial application. In other words, the issuance of a press release leads to over 10 times higher likelihood of a paper being used in commercial applications.

The coefficients for *Patent Citations* and *Log(Patent Cites+1)* are positive and significant. Model (5), which examines the effect on the count of patent citations, shows a coefficient of 13.05. This indicates that papers receiving a press release garner, on average, 13 additional citations from firm-owned patents compared to those without press coverage. For *Log(Patent Cites+1)*, the coefficient is 1.618, which can be interpreted as an approximation of semi-elasticity. However, it's important to note that this coefficient is sensitive to the selection weight used in the logarithmic transformation (Chen and Roth, 2024). In appendix A1, I provide the estimates by specifying the weights on extensive and intensive margins and find similar positive results.

These results show that receiving a press release leads to increase in both the likelihood of the paper being cited by at least one firm owned patent as well as the total number of patent citations that a paper receives.

5.5 Robustness

I do several robustness checks to further validate these findings. Firstly, the instrument is based on the observation that press offices typically post press releases around the time of paper publication. However, during congested periods, they may delay press releases for important papers, working on them during less busy times. Alternatively, they might prepare press releases for upcoming papers in advance during quieter weeks. To account for this potential workload smoothing, I provide additional results in Table A2, where I vary the time window used to calculate the instrument. Instead of computing the PIO congestion at a weekly level, I compute congestion over 2-, 3-, and 5-week windows around the publication of the focal paper. The strength of the first-stage relationship decreases as the window expands: F-Stat changes from 48 for the 2-week window to 19 for the 3-week window and 9.7 for the 5-week window. Notably, the 5-week window results in a weak instrument, as its F-statistic falls below the critical value of 10, and I do not find any significant effects for this window. I replicate the main results and find strong positive results for the effect of a press release on patent citations with instruments using 2- and 3-week windows instead of 1-week windows.

Second, I address concerns about author prestige, which could influence both press coverage likelihood and commercial application of research. I include author fixed effects in the analysis. I show the first stage relationship between the *Congestion Index* and the likelihood of a paper receiving a press release in figure 6. I find a strong negative relationship between the two, and F-Stat is above 50 for models that include last or first-author fixed effects. Appendix table A3 shows the main result with last author and first author fixed effects, along with Year-Month, Journal-Year, and Field-Year fixed effects. The main findings remain robust under these specifications. Models 1, 3, and 5, controlling for last-author fixed effects, show that the coefficients for the Press Release (0/1) variable remain positive and significant. When switching to first author fixed effects in Models 2, 4, and 6, the press release coefficients slightly increase. These results demonstrate that the main finding—the

positive impact of press releases on commercial applications— is robust to controlling for individual author effects.

Third, I develop an alternative measure of the use of scientific knowledge in commercial applications by tracking the introduction of new words in scientific papers and their subsequent use in patents. Using data from Arts et al. (2024), I identify all papers in my sample that introduced a new word. Next, I track patents that incorporate these scientific discoveries by identifying the use of the new words in the patents' titles, abstracts, and claims. Approximately 7.7% of the papers in the sample introduced a new word. As shown in Table B5, I find consistent results: papers that introduced new words and received a press release are six times more likely to be used in commercial applications.

6 Mechanism: Scientific Translation

Press coverage can help in the diffusion of knowledge in a few different ways. Firstly, the press can direct firms' attention to new scientific papers they would have missed otherwise. The volume of scientific papers published is large, which makes it difficult for anyone to stay updated on all the recent advances (Jones, 2009; Chu and Evans, 2021). Media coverage can selectively highlight new research, bringing it to the attention of firms and the wider public. Secondly, coverage in the press, particularly in the national press, can serve as a validation of scientific research and its potential impact, lending it greater credibility and leading to higher use (Freedman et al., 2015; Bikard, 2018; Krieger et al., 2024). Press can also act as a translator by presenting the scientific knowledge in simpler and non-technical language and can convey findings in a more accessible manner.

I explore the role of press and science communication in translating complex scientific findings by examining the complexity inherent within scientific language. I build on advancements in Natural Language Processing (NLP) to identify technical vocabulary that, while streamlining communication within specific sub-fields, potentially hinders the broader dissemination of ideas across disciplines. Drawing on the work by Lucy et al. (2023), who developed a model from an analysis of over 12 million scientific abstracts to identify discipline-specific "jargon" words. I categorize scientific papers based on their use of specialized language, distinguishing those with minimal technical terminology as having *low specialized language* and those abundant in such terminology as having *highly specialized language*.

Using these data, I test Hypothesis 2, which proposes that the benefits of scientific translation are greater for scientific papers that use more specialized language. I focus on a subset of scientific papers for which abstracts are available, accounting for 38% of the sample. [1] In appendix table C1, I provide the summary statistics for the sub-sample of papers for which an abstract is available. This subsample, while representative of the full dataset in terms of likelihood of receiving press releases (3.1% vs 2.9%), mean number of co-authors (5.4 vs 5.6), and mean number of institutional affiliations (2.4 vs 2.5), exhibits a notably higher average of patent citations (0.929 vs 0.572). Results presented in Table C2 demonstrate that the effect of press releases on this subsample is positive and of greater magnitude compared to the full sample.

I use the following regression model to evaluate the benefit of scientific translation:

[1] OpenAlex does not provide abstracts for all papers due to copyright and licensing issues.

$$\begin{aligned} \textit{Patent Citations}_i = \beta_0 \times \widehat{\textit{Press Release}}_i + \beta_1 \times \widehat{\textit{Press Release}}_i \times \textit{Specialized Lang: Med} \\ + \beta_2 \times \widehat{\textit{Press Release}}_i \times \textit{Specialized Lang: High} + X_i + \rho_{ft} + \gamma_{jt} + \eta_t + \varepsilon_{ifjt} \end{aligned} \quad (6)$$

In this model, β_0 captures the baseline effect of a press release on patent citations when the focal paper's usage of specialized language is at the reference level (*Specialized Language: Low*). The coefficients β_1 and β_2 represent the interaction effects between *Press Release* and *Specialized Language: Medium* and *High*, respectively. These interactions show how the impact of a press release on patent citations differs when the specialized language is at medium or high levels compared to the baseline low level. If scientific translation is an important mechanism, we would expect both β_1 and β_2 to be positive, indicating that press releases have a stronger effect on patent citations for papers with higher levels of specialized language.

Table 6 shows the results of the effect of the press releases on patent citations moderated by the use of specialized language. For both *Patent Cite (0/1)* and *Log(Patent Cite +1)*, the effect of the press release is higher for papers that use more specialized language in their abstracts. In model (1), the coefficient for *Press Release (0/1)* is 0.684, which is not statistically significant ($p > 0.05$), suggesting that papers that use simple language do not benefit from press release coverage. The coefficients for the interaction terms *Press Release* $\times$ *Specialized Language:Mid* and *Press Release* $\times$ *Specialized Language:High* are increasing and significant. The effect is most pronounced for papers with a high level of specialized language, evidenced by a coefficient of 0.868, also significant at the 1% level. These results suggest that the effect of a press release is moderated by the complexity of language in the paper's abstract.

Model (2) presents the results for a log-transformed count of citations, showing a baseline effect of press releases (1.981, $p < 0.05$), indicating that issuing a press release can significantly increase the number of citations a patent receives. The interaction terms further illustrate that the effect of the press release is higher for the paper using mid-level (0.491, $p < 0.05$) and high-level (1.147, $p < 0.01$) specialized language, aligning with the findings from the binary citation model. These findings corroborate the hypothesis that press coverage is particularly beneficial for papers that use more specialized language, underscoring that scientific translation is an important mechanism.

In appendix table C4, I use a continuous measure of the use of specialized language (percentage of jargon words in the abstract) and control for baseline differences in the use of specialized language, and I find similar results – the effect of scientific translation is higher for papers that use more specialized language.

These results show that the benefit of a press release is higher for papers that use more specialized language, but they should not be interpreted as causal effects. Several factors could influence this relationship, including the inherent quality of the research, the specific nature of the technology described, and strategic language choices by researchers. For instance, higher-quality research might naturally use more complex language while also being more likely to have commercial applications. Similarly, certain technologies might require specialized terminology while also having greater commercial potential. Researchers might also deliberately adjust their language complexity based on their expectations of impact, using more specialized terms to enhance perceived rigor or simplifying language to broaden appeal.

7 Scientific Translation: Substitute or Complement to Scientific Capabilities?

Next, I investigate whether scientific translation acts as a substitute for or complement to firm expertise. To operationalize the scientific expertise of a firm, I utilize the recently developed PQR dataset (Scharfmann et al., 2024). This dataset identifies scientist-inventors (SI) – individuals who have authored both scientific papers and patents. I gather all patents and academic publications of SIs. I infer the place of employment from the assignee information listed on their patents. From this data, I construct a panel of firms incorporating information about the scientist-inventors, their patents, and their publications. I use this panel to identify the expertise of each firm across different scientific subfields. Specifically, I define a firm's expertise in a scientific subfield based on whether any of its scientist-inventor employees have published a paper in that subfield within the past three years.

7.1 Do Scientific Translations Substitute Scientific Expertise?

I use PQR data to test Hypothesis 3a, which posits that the benefits of scientific translation are greater for firms with prior scientific capabilities. I identify scientific capability at the level of inventor teams within firms. Specifically, I classify inventor teams that have at least one scientist-inventor as having prior scientific capability. I then categorized all patent citations to papers in the sample into two groups: citations from patents with scientist-inventor co-authors and citations from patents with inventor-only teams. This classification enables a comparison of how scientific translation impacts teams that differ in prior scientific expertise.

Table 7 presents regression results comparing the impact of press releases on teams with and without prior scientific expertise. Models (1) and (2) focus on the effect of a press release for non-SI and SI teams, respectively. The coefficient on the press release is positive in both models, indicating that the press release benefits both SI and non-SI inventor teams. However, the magnitude of the coefficient varies between the two. Specifically, the coefficient for non-SI teams is 0.718 ($p < 0.01$). For SI teams, the coefficient is about 3.4 times larger. The results show that while both SI and non-SI teams benefit from a press release, the effect is higher for teams that have prior scientific expertise.

In models (3) and (4), I focus on the role of scientific translation. While scientific translation can help inventor teams by making it easier to understand new scientific breakthroughs, however, their lack of prior scientific expertise can limit their use of the translated knowledge. Results show that for teams lacking prior scientific expertise (model 3), the benefit of scientific translation is marginal, showing a small increase of 16% (coefficient 0.153, $p < 0.1$) for papers using highly specialized language over the baseline. However, for teams with prior scientific capability, the benefit of the press release is higher for papers that use more specialized language. Compared to the baseline, papers using low specialized language, those with medium specialized language see an additional 56% gain in patent citations, while highly specialized papers experience an 184% increase.

These results demonstrate that science communication and translations are substantially more beneficial to inventor teams with existing scientific expertise, likely due to their enhanced ability to leverage the translated knowledge. Importantly, these results indicate that scientific translation does not replace the need for prior scientific expertise. While translation can make complex science more accessible, a team's capacity to innovate using this knowledge still depends heavily on their existing scientific capabilities. In essence, scientific translations through the press are not a substitute for scientific expertise.

7.2 Scientific Translation: Complement to Firm's Scientific Expertise

Although scientific translations are not a substitute for scientific expertise, they may complement a firm's existing capabilities. To explore this potential, I investigate how translations affect firms' utilization of science across various scientific domains. Specifically, I test Hypothesis H3b, which posits that scientific translations provide greater benefits in fields where the firm lacks prior expertise.

To conduct this analysis, I aggregate scientist-inventor (SI) publication data at the firm level, allowing for a comparison between scientific areas in which firms have prior expertise and those where it has limited experience. Specifically, I identify each firm's scientific expertise in an area based on academic publications of its scientist-inventors. Patent citations made by a firm are then classified into two categories: *In-Field* citations, where at least one scientist-inventor at the firm had published a paper related to the cited scientific concepts in the focal paper within the past three years, and *Out-of-Field* citations, where no scientist-inventor at the firm had published on the related concepts. This classification allows for a comparison of how firms utilize translated scientific knowledge in familiar versus unfamiliar scientific domains.

Table 8 shows the effect of a press release on patent citations disaggregated by prior expertise. For firms with expertise in a field, a press release is associated with a 41.5% increase in patent citations, significant at the 10% level. This indicates that firms with existing scientific capabilities in an area benefit from press releases. However, the interaction effects between press releases and the use of specialized language (both "Mid" and "High") do not show significant effects. The coefficients for "Press Release (0/1) Specialized Language: Mid" (-0.017) and "Press Release (0/1) Specialized Language: High" (0.063) are close to zero and statistically insignificant. This suggests that for firms with expertise, the level of specialized language used in a paper does not substantially modify the effect of the press release on patent citations. For such firms, scientific translation is not as important as they already possess the capability to understand and evaluate scientific content in their areas of expertise.

In contrast, for firms without expertise in the area (Column 2), the results highlight the role of scientific translation in determining the usefulness of press releases. The base effect of issuing a press release alone is modest (coefficient: 0.127) and not statistically significant, implying that, on average, firms without prior expertise do not benefit a press release when the paper uses simple language. However, the coefficient for the interaction term "Press Release (0/1) Specialized Language: Mid" is 0.118, which corresponds to an additional 12.5% increase in patent citations, significant at the 10% level. The effect is even stronger for the "High" level of specialized language, with a coefficient of 0.321, indicating an additional 37.8% increase in patent citations, significant at the 1% level. These findings show that the benefits of scientific translation are greater in scientific fields in which the focal firm does not have prior expertise. Overall, these results highlight that while science communication through press releases cannot substitute for a firm's scientific expertise, it can complement it, particularly when firms venture into scientific fields where they lack prior expertise.

8 Conclusion

Innovation and management research has extensively researched how firms can build capabilities to use science for commercial gains (Cohen and Levinthal, 1990; Rosenberg, 1989; Arora and Gambardella, 1994). While these demand-side interventions are crucial, in this paper, I introduce a new supply-side channel - science

communication through the press that can help firms in understanding new scientific advances, thereby increasing the commercial use of science. To investigate this phenomenon, I build a new dataset that matches press releases to scientific publications. Employing a novel empirical design that exploits congestion at university press offices, I provide the first empirical evidence of the effect of scientific communication through press releases on the commercial use of science. My results show that scientific papers that receive a press release are much more likely to be used by firms. Furthermore, I find support for the importance of scientific translation –communication of science using a simple, non-technical language, as an important mechanism. My results show that the effect of a press release is higher for papers that use more specialized language.

While scientific translations can facilitate firms' understanding of new scientific knowledge, I find that a firm's ability to utilize such knowledge is tied to its existing scientific expertise (Cohen and Levinthal, 1990). I provide empirical evidence supporting my theoretical framework that positions scientific translation as a complement to, rather than a substitute for, a firm's scientific capabilities. The results show that inventor teams within firms benefit more from scientific translations when they include a co-inventor who has published academic papers, indicating the importance of pre-existing scientific engagement. Notably, I find no evidence that scientific translation offers any benefits to firms in scientific domains where they already possess expertise, as they likely have the capacity to understand and evaluate new discoveries in these areas. Instead, the positive impact of scientific translation is only observed in fields where firms lack prior expertise. This relationship underscores the complementary nature of scientific translation, suggesting it is most effective in expanding a firm's innovative capabilities into new domains.

The paper addresses a fundamental challenge in the innovation process: how to make complex, specialized scientific knowledge more accessible to firms (Allen, 1984; Cohen et al., 2002). While the prior literature on the commercialization of science has focused on various demand-side interventions, including internal R&D (Rosenberg, 1989; Gambardella, 1992), strategic hiring(Almeida and Kogut, 1999; Hsu et al., 2024), and collaborative partnerships to acquire scientific knowledge(Cockburn and Henderson, 1998; Zucker et al., 2002), these channels can be resource-intensive and may not be available to all firms across different domains of science. This paper contributes to the literature on science commercialization by demonstrating that science communication through the press, which is widely available, can help firms build upon scientific knowledge.

The paper adds to the work on scientific capabilities in firms in three key ways Cohen and Levinthal (1990). First, it underscores the importance of prior scientific engagement in a firm's ability to understand and exploit new scientific advances. Second, it highlights a key distinction between a firm's capacity to understand and evaluate scientific knowledge and its capacity to apply this knowledge commercially. While scientific translations can facilitate understanding and evaluation of new scientific developments, firms still require scientific capabilities to actually innovate and build upon these advances. Third, the paper highlights the complementary role of scientific translations in a firm's innovation process. While a firm's existing scientific capabilities remain crucial for innovation, the paper shows that scientific translations can serve as a bridge, helping firms understand scientific advances in fields where they lack prior expertise.

The study also contributes to a parallel body of work on science communication and its impact on the diffusion of scientific knowledge (Kiernan, 2003; Fischhoff and Scheufele, 2013; Fischhoff, 2019b). Recent papers in science communication have shown a positive association between press coverage of scientific findings and

the subsequent citations these papers receive in academic literature. However, finding causal evidence for the effect of press release coverage on the diffusion of science has been challenging. This paper makes a significant methodological contribution by providing new data and an empirical design that allows for the identification of causal relationships between press release coverage and the diffusion of scientific knowledge. Additionally, the study contributes to the growing body of work examining the role of language in science evaluation and use(Lerchenmueller et al., 2019; Peng et al., 2024). It extends this line of inquiry by demonstrating that the language of science plays a crucial role not just within academia but also in the diffusion of scientific knowledge to industry.

Despite its contributions, this study has several limitations. Firstly, the full effect of science communication through the press may not be entirely captured due to the lack of comprehensive data on media coverage of science. While press releases are a crucial source for science journalists, other channels like social media or direct communications from scientists also play a role in disseminating scientific news. The absence of data on overall media coverage and its volume may impact the results. Second, the use of specialized language in scientific papers is not random and may be influenced by factors such as the norms of specific scientific disciplines or the complexity of the subject matter. This limits the causal interpretations of the findings related to scientific language complexity. Thirdly, the study doesn't address the qualitative differences in press releases across various Public Information Offices or individual writers, which could significantly influence how effectively scientific knowledge is translated and utilized by firms. Fourth, the study does not identify the specific mechanisms within firms that benefit from this translation, leaving it unclear whether the primary advantage is helping technical staff understand new developments or enabling non-technical decision-makers to engage more directly with science. Lastly, while the study focuses on the positive impacts of press releases, it overlooks potential negative effects. For instance, oversimplification in press releases could lead to misunderstandings or misapplications of scientific concepts, potentially resulting in inefficient or misguided commercial efforts. These limitations highlight areas for future research.

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9 Tables

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Press Release (0/1)	2,687,312	0.029	0.168	0	1
Patent Citation (0/1)	2,687,312	0.080	0.271	0	1
Patent Citations	2,687,312	0.572	9.726	0	4,955
Log(PatentCites+1)	2,687,312	0.115	0.465	0.000	8.508
PIO Congestion	2,687,312	0.710	1.117	−1.9	7.1
N. Authors	2,687,312	5.606	5.038	1	100
N. Affiliations	2,687,312	2.515	2.500	1	92

Press Release (0/1) is a binary variable indicating if a press release about the paper was posted to EurekAlert or not. *Congestion Index* is the instrument variable that combines the congestion faced by the paper across all university press offices that could have posted a press release. *N. Authors* is the number of co-authors, *N. Affiliations* is the number of unique affiliations of the co-authors.

Table 2: OLS Estimates: Effect of press releases on citations from firm-owned patents

Dependent Variables:	Patent Citation (0/1)				Patent Citations	Log(Patent Cites+1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Press Release (0/1)	0.1220***	0.0992***	0.0969***	0.0506***	0.6970***	0.0954***
	(0.0029)	(0.0024)	(0.0024)	(0.0018)	(0.0585)	(0.0039)
N. Authors		0.0070***	0.0065***	0.0040***	0.0502***	0.0072***
		(0.0002)	(0.0002)	(0.0002)	(0.0038)	(0.0003)
N. Affiliations		-0.0068***	-0.0053***	-0.0026***	-0.0425***	-0.0052***
		(0.0003)	(0.0002)	(0.0002)	(0.0050)	(0.0003)
Fixed-effects						
Year-Month	✓	✓	✓	✓	✓	✓
Field-Year			✓	✓	✓	✓
Journal-Year				✓	✓	✓
Fit statistics						
Observations	2,687,312	2,687,312	2,687,312	2,687,312	2,687,312	2,687,312

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: PIO Selection – Estimates of the likelihood of a paper to receive a press release based on its scientific and commercial potential

Dependent Variable:	Press Release (0/1)						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Commercial Potential	0.0172***	-0.0031***	-0.0042***				-0.0106***
	(0.0005)	(0.0006)	(0.0007)				(0.0007)
Scientific Potential				0.0564***	0.0261***	0.0380***	0.0417***
				(0.0008)	(0.0009)	(0.0011)	(0.0011)
Constant	0.0276***			-0.0052***			
	(0.0003)			(0.0006)			
Fixed-effects							
Journal		✓			✓		
Journal-Year			✓			✓	✓
Field-Year			✓			✓	✓
Year-Month			✓			✓	✓
Fit statistics							
Observations	1,561,665	1,561,665	1,561,665	1,561,665	1,561,665	1,561,665	1,561,665

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table shows the relationship the likelihood of press release issuance and the commercial and scientific potential of a paper. I use data from Masclans et al. (2023) who have used a machine learning based algorithm to measure the commercial and scientific potential of papers. The results show that PIOs use journal prestige to identify high quality research. However, for papers published in the same journal, PIOs prioritize papers with high scientific potential and are less likely to select papers that have high commercial relevance.

Table 4: First Stage: Effect of press office congestion on the likelihood of a paper receiving a press release

Dependent Variable:	Press Release (0/1)			
Model:	(1)	(2)	(3)	(4)
Congestion Index	-0.0045***	-0.0033***	-0.0047***	-0.0016***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
N. Authors		0.0063***	0.0060***	0.0043***
		(0.0001)	(0.0001)	(0.0001)
N. Affiliations		-0.0016***	-0.0012***	-0.0002*
		(0.0001)	(0.0001)	(0.0001)
Fixed-effects				
Year-Month	✓	✓	✓	✓
Field-Year			✓	✓
Journal-Year				✓
Fit statistics				
Observations	2,687,312	2,687,312	2,687,312	2,687,312

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the relationship between the congestion faced by a paper (measured by the *Congestion Index*) and the likelihood of it receiving a press release during that week. *Congestion Index* is calculated based on the number of papers published in fields other than the focal paper's field by scientists affiliated with the same university as the paper's co-authors. For papers with co-authors from multiple universities, the index takes the value of the least congested press office.

The coefficient in column (4) indicates that a one standard deviation increase in the *Congestion Index* is associated with a 6% decrease in the likelihood of a paper receiving a press release.

Table 5: 2SLS: Effect of press release on patent citations from firms

Dependent Variables:	Patent Citation (0/1)				Patent Citations	Log(Patent Cites+1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Press Release (0/1)	0.402***	0.396***	0.924***	0.839***	13.050**	1.618***
	(0.105)	(0.143)	(0.070)	(0.188)	(5.328)	(0.325)
N. Authors		0.005***	0.002***	0.001	-0.003	0.001
		(0.001)	(0.000)	(0.001)	(0.023)	(0.001)
N. Affiliations		-0.006***	-0.004***	-0.002***	-0.040***	-0.005***
		(0.000)	(0.000)	(0.000)	(0.006)	(0.000)
Fixed-effects						
Year-Month	✓	✓	✓	✓	✓	✓
Field-Year			✓	✓	✓	✓
Journal-Year				✓	✓	✓
Fit statistics						
Observations	2,687,312	2,687,312	2,687,312	2,687,312	2,687,312	2,687,312
F-test (1st stage)	2,031	1,129	2,165	141	141	141

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the effect of press releases on firm-owned patent citations. Column (4) shows the coefficient for any patent citation. The coefficient of 0.839 indicates that a press release increases the likelihood of a paper receiving at least one patent citation by 84% percentage points, which is a 10x increase over the baseline. The coefficient in column (5) indicates that a press release leads to 13 additional cites.

Table 6: Effect of the press release on patent citations from firms moderated by the use of specialized language in the paper's abstract.

Dependent Variables:	Patent Citation (0/1)	Log(Patent Cites+1)
Model:	(1)	(2)
Variables		
Press Release (0/1)	0.684	1.981*
	(0.604)	(1.091)
Press Release (0/1) × *Specialized Language: Mid*	0.468***	0.491**
	(0.124)	(0.205)
Press Release (0/1) × *Specialized Language: High*	0.868***	1.147***
	(0.158)	(0.265)
N. Authors	0.001	-0.001
	(0.003)	(0.005)
N. Affiliations	-0.002***	-0.006***
	(0.000)	(0.001)
Fixed-effects		
Subfield-Year	✓	✓
Year-Month	✓	✓
Journal-Year	✓	✓
Fit statistics		
Observations	1,020,091	1,020,091

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The coefficient for *Specialized Language: Medium* and *Specialized Language: High* are positive, which indicates that paper that use more complex language benefit more from press coverage. The classification of papers into specialized language categories is based on their usage of sub-field-specific technical words in abstracts compared to other papers published in the same journal, sub-field, and year. The reference category is *Specialized Language: Low*
I provide additional results using a continuous measure of the use of specialized language in appendix table C3. I find similar results.

Table 7: Effect of press release for papers disaggregated by prior scientific engagement of inventor-team

	Log(Patent Cites + 1)			
Model:	Non-SI Team (1)	SI Team (2)	Non-SI Team (3)	SI Team (4)
Variables				
Press Release (0/1)	0.718*	2.502***	0.661	1.960*
	(0.374)	(0.946)	(0.417)	(1.046)
Press Release (0/1) × *Specialized Language: Mid*			0.026	0.450**
			(0.078)	(0.194)
Press Release (0/1) × *Specialized Language: High*			0.153*	1.044***
			(0.089)	(0.250)
N. Authors	0.000	-0.001	0.000	-0.001
	(0.002)	(0.005)	(0.002)	(0.005)
N. Affiliations	-0.002***	-0.005***	-0.002***	-0.005***
	(0.000)	(0.001)	(0.000)	(0.001)
Fixed-effects				
Subfield-Year	✓	✓	✓	✓
Year-Month	✓	✓	✓	✓
Journal-Year	✓	✓	✓	✓
Fit statistics				
Observations	1,020,091	1,020,091	1,020,091	1,020,091

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table shows the results for the effect of press coverage disaggregated by the inventor team's scientific expertise. Scientist Inventor (SI) teams consist of inventor teams with at least one scientist – an inventor who has published at least one scientific publication. Non-SI teams do not have any scientist-inventors.
I find that SI teams benefit more from press releases (columns 1 and 3). Moreover, the benefit of scientific translations is also higher for SI teams (column 3). The results suggest that teams need prior scientific capability in order to benefit from science translation through press releases.

Table 8: Effect of press release disaggregated by firm's prior scientific expertise in a scientific field

	Log(Patent Cites + 1)	
	(1) Firms with expertise in the area	(2) Firms without expertise in the area
Press Release (0/1)	0.415*	0.127
	(0.250)	(0.309)
Press Release (0/1) × *Specialized Language: Mid*	-0.017	0.118*
	(0.044)	(0.062)
Press Release (0/1) × *Specialized Language: High*	0.063	0.321***
	(0.053)	(0.083)
Controls	✓	✓
Fixed-effects		
Subfield-Year	✓	✓
Year-Month	✓	✓
Journal-Year	✓	✓
Fit statistics		
Observations	1,020,091	1,020,091

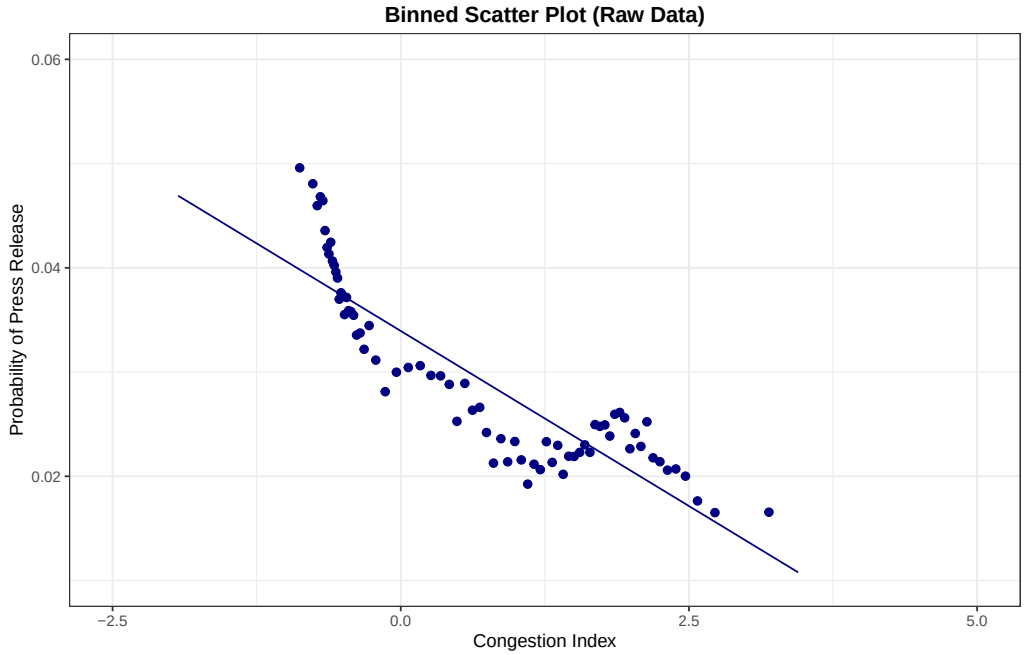
Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table shows the results for the effect of press coverage disaggregated by the firm's prior expertise in a scientific area. I use the PQR dataset to identify publications of scientists working at a firm in any given. Firm expertise is based on the areas of publication of the scientists at the firm.

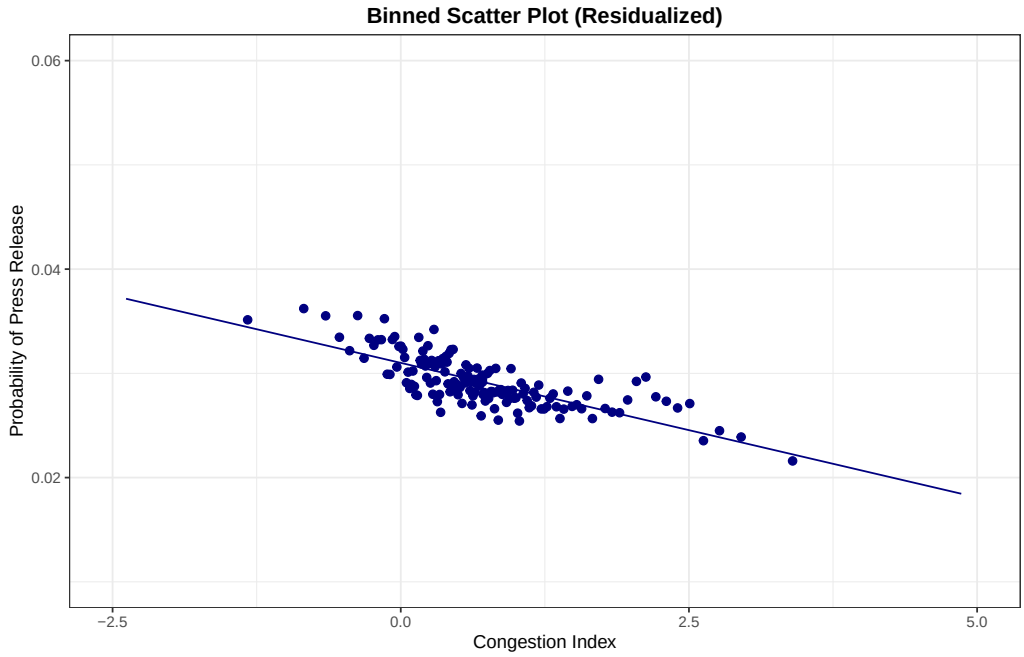
I find no effect of scientific translation (Column 1) for firms that have prior scientific expertise in an area. The effect is driven by patent citations from firms who lack prior expertise in a scientific area (column 2).

Figure 2: First Stage Relationship

(a) First Stage Relationship (Raw Data)



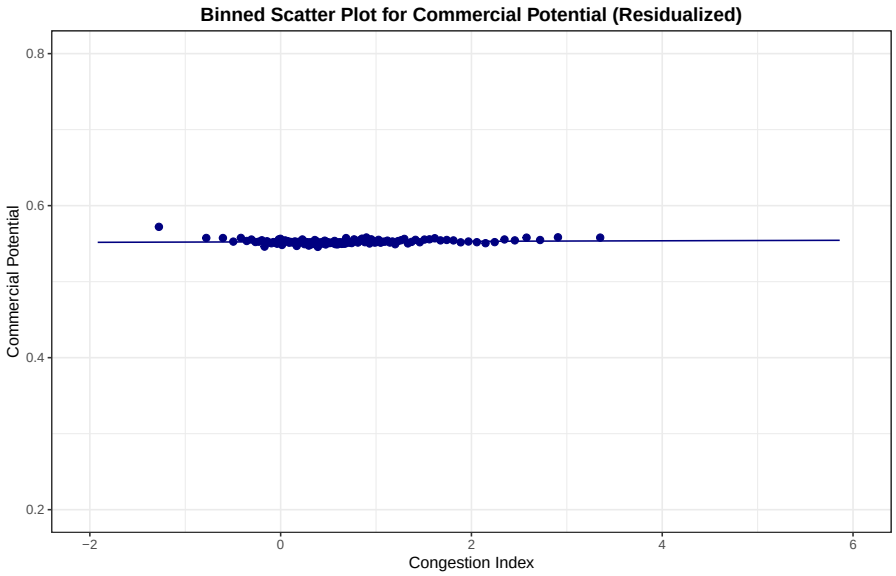
(b) First Stage Relationship (Adjusted)



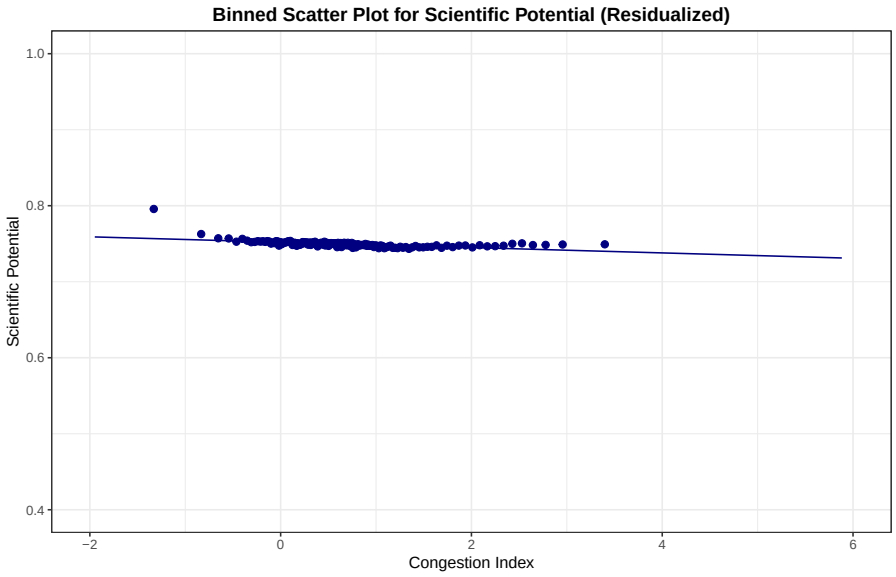
Note: Panel (a) represents the unadjusted relationship between the variables, while panel (b) shows the adjusted relationship accounting for fixed effects and controls. The figures show a negative relationship between *Congestion Index* (instrument variable) and the likelihood of papers receiving a press release (dependent variable). One *sd* change in the instrument is linked to 6% change in the likelihood of a paper receiving a press release.

Figure 4: Variation in commercial and scientific potential of papers published during weeks with different congestion

(a) Commercial Potential



(b) Scientific Potential



The figure shows the variation in commercial and scientific potential of papers against the instrument *Congestion Index*. I use data from Masclans et al. (2023) to measure commercial and scientific potential of papers. Panel (a) shows that there is no identifiable relationship between commercial potential and the instrument, suggesting that papers with high commercial potential are not systematically published in weeks with higher or lower congestion. However, panel (b) shows a negative relationship between scientific potential and congestion. Papers with higher scientific potential tend to be published in weeks with lower congestion at university press offices.

A Appendix: Robustness

Table A1: 2SLS: Effect of press release on patent citations from firms. I use the following transformation $m(y) = log(y)$ for $y > 0$ and $m(0) = -x$

Dependent Variables:	$log(PatentCites)$ $x = 1$	$log(PatentCites)$ $x = 0.1$	$log(PatentCites)$ $x = .01$
Model:	(1)	(2)	(3)
Variables			
Press Release (0/1)	2.207***	1.452***	1.377***
	(0.4474)	(0.3040)	(0.2911)
N. Authors	0.0010	0.0004	0.0003
	(0.0019)	(0.0013)	(0.0012)
N. Affiliations	-0.0066***	-0.0044***	-0.0042***
	(0.0005)	(0.0003)	(0.0003)
Fixed-effects			
Field-Year	✓	✓	✓
Year-Month	✓	✓	✓
Journal-Year	✓	✓	✓
Fit statistics			
Observations	2,687,312	2,687,312	2,687,312

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A2: Effect of press release on patent citations using different time windows to measure PIO congestion (instrument).

Dependent Variables:	Patent Citation (0/1)			Patent Citations			Log(Patent Cites+1)		
Time-span for instrument:	2 Weeks	3 Weeks	5 Weeks	2 Weeks	3 Weeks	5 Weeks	2 Weeks	3 Weeks	5 Weeks
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Press Release (0/1)	1.788***	1.795***	-0.126	21.788**	38.249***	1.951	2.759***	3.105***	0.270
	(0.390)	(0.627)	(0.537)	(9.964)	(14.524)	(15.236)	(0.629)	(1.051)	(0.942)
N. Authors	-0.003*	-0.003	0.005**	-0.034	-0.100*	0.045	-0.004	-0.005	0.006*
	(0.002)	(0.002)	(0.002)	(0.040)	(0.058)	(0.061)	(0.003)	(0.004)	(0.004)
N. Affiliations	-0.001***	-0.001***	-0.003***	-0.028***	-0.017	-0.040***	-0.003***	-0.003***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.009)	(0.012)	(0.011)	(0.001)	(0.001)	(0.001)
Fixed-effects									
Field-Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month	✓	✓	✓	✓	✓	✓	✓	✓	✓
Journal-Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics									
Observations	2,677,210	2,677,210	2,677,210	2,677,210	2,677,210	2,677,210	2,677,210	2,677,210	2,677,210
F-test (1st stage)	48.280	18.836	9.7345	48.280	18.836	9.7345	48.280	18.836	9.7345

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

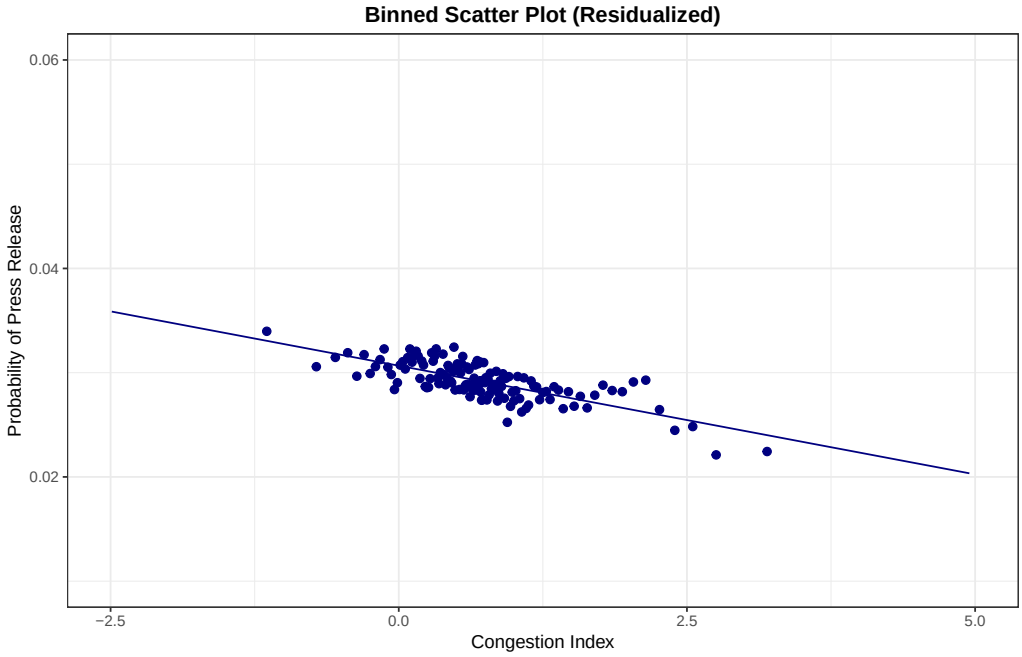
Table A3: Effect of Press Release on Patent Citations with Author Fixed-Effects

Dependent Variables:	Patent Citation (0/1)		Patent Citations		Log(Patent Cites+1)	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Press Release (0/1)	0.980***	1.228***	6.800	18.627*	1.853***	2.181***
	(0.332)	(0.385)	(9.502)	(10.145)	(0.577)	(0.639)
N. Authors	-0.002	-0.002	0.005	-0.046	-0.003	-0.004
	(0.002)	(0.002)	(0.049)	(0.055)	(0.003)	(0.003)
N. Affiliations	-0.001**	-0.001**	-0.016*	-0.020*	-0.002***	-0.002***
	(0.000)	(0.000)	(0.008)	(0.011)	(0.001)	(0.001)
Fixed-effects						
Field-Year	✓	✓	✓	✓	✓	✓
Year-Month	✓	✓	✓	✓	✓	✓
Journal-Year	✓	✓	✓	✓	✓	✓
Last Author	✓		✓		✓	
First Author		✓		✓		✓
Fit statistics						
Observations	2,464,987	2,687,769	2,464,987	2,687,769	2,464,987	2,687,769
F-test (1st stage)	51.973	51.023	51.973	51.023	51.973	51.023

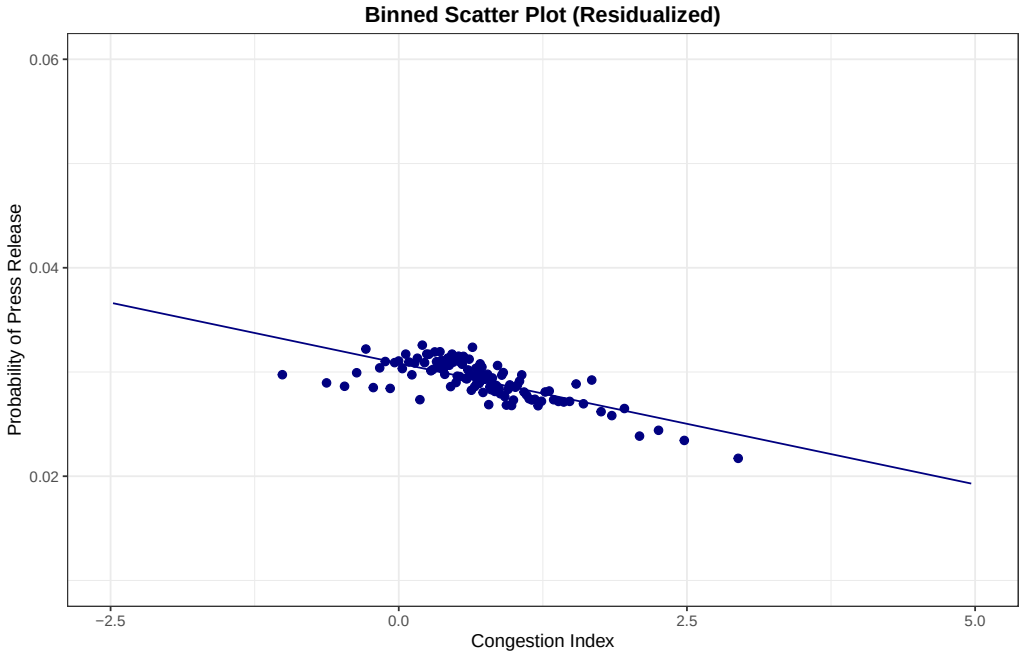
Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 6: First Stage Relationship with Author Fixed-Effects

(a) First Stage Relationship with Last Author Fixed-Effects



(b) First Stage Relationship with First Author Fixed-Effects



B Using Adoption of New Words to Measure Commercial Use of Science

I measure the diffusion of scientific knowledge into commercial applications by tracking the emergence of new words in academic papers and their use in patents. I utilize data from Arts et al. (2024) to identify academic papers that introduce new terminology to scientific literature, finding that 206,528 papers (7.7% of my sample) introduced at least one new word. These linguistic innovations serve as markers of novel concepts, techniques, or discoveries that represent scientific advances. I then examine how these newly introduced scientific terms were used for new inventions, specifically analyzing their appearance in patent titles, abstracts, and claims. By tracking the adoption of new words in patent literature, I quantify diffusion of knowledge from academia to industry using a non-citation based measure.

Table B4: Summary Statistics: New-Word Adoption

Statistic	N	Mean	St. Dev.	Min	Max
Press Release (0/1)	206,528	0.038	0.192	0	1
Any Patent Adoption (0/1)	206,528	0.049	0.216	0	1
N. Patent Adoption	206,528	0.270	6.701	0	1,015
Log(Patent Adoption+1)	206,528	0.060	0.314	0.000	6.924

Table B5: Effect of Press Release on Commercial Use of Science Measured Using New-Word Adoption

Dependent Variables:	Any Patent Adoption (0/1)	N. Patent Adoption	Log(Patent Adoption+1)
Model:	(1)	(2)	(3)
Variables			
Press Release (0/1)	0.2986***	5.285**	0.4036***
	(0.0754)	(2.271)	(0.1091)
N. Authors	-0.0010*	-0.0356**	-0.0014*
	(0.0006)	(0.0179)	(0.0008)
N. Affiliations	-0.0006*	0.0124	-0.0005
	(0.0003)	(0.0089)	(0.0004)
Fixed-effects			
Field-Year	✓	✓	✓
Year-Month	✓	✓	✓
Fit statistics			
Observations	206,528	206,528	206,528
F-test (1st stage)	248.95	248.95	248.95

Clustered (YW) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table shows the results for papers that introduced new words. *Any Patent Adoption* is a binary variable indicating if any patent used the new word that was introduced by the focal paper. *N. Patent Adoption* is the count of papers that used a new word introduced by the focal paper. *Log(Patent Adoption+1)* is the logarithm of *N. Patent Adoption*.
Using the New-Words measure, I find similar results. Papers that introduced new words and received a press release are six times more likely to have their new terminology adopted in commercial applications.

C Translation: Papers with Abstract

Table C1: Summary Statistics Comparison of Main Sample and Papers with Abstract

	Main Sample		**Papers with Abstract**	
Variable	**Mean**	**SD**	**Mean**	**SD**
Press Release (0/1)	0.029	0.168	0.031	0.173
Patent Citation (0/1)	0.080	0.271	0.131	0.337
Patent Citations	0.572	9.726	0.929	11.141
N. Affiliations	2.515	2.500	2.402	2.226
N. Authors	5.606	5.038	5.448	4.491
Journal IPP	5.790	7.181	5.750	6.745

Table C2: Effect of the press release on patent citations from firms for the subset of papers that have abstracts in OpenAlex.

Dependent Variables:	Patent Citation (0/1)	Patent Citations	Log(Patent Cites+1)
Model:	(1)	(2)	(3)
Variables			
Press Release (0/1)	1.188**	20.429	2.575***
	(0.536)	(13.755)	(0.982)
N. Authors	0.000	-0.011	-0.001
	(0.003)	(0.067)	(0.005)
N. Affiliations	-0.003***	-0.054***	-0.006***
	(0.000)	(0.015)	(0.001)
Fixed-effects			
Subfield-Year	✓	✓	✓
Year-Month	✓	✓	✓
Journal-Year	✓	✓	✓
Fit statistics			
Observations	1,020,091	1,020,091	1,020,091
F-test (1st stage)	23.354	23.354	23.354

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C3: Effect of press release on patent citations moderated by the use of specialized language

Dependent Variables:	Patent Citation (0/1)	Log(Patent Cites+1)
Model:	(1)	(2)
Variables		
Press Release (0/1)	0.416	1.196
	(0.497)	(0.901)
% Specialized Words	0.022	0.052*
	(0.017)	(0.031)
Press Release (0/1) × % Specialized Words	2.423***	4.309***
	(0.580)	(1.099)
N. Authors	0.000	-0.001
	(0.003)	(0.005)
N. Affiliations	-0.002***	-0.005***
	(0.000)	(0.001)
Fixed-effects		
Subfield-Year	✓	✓
Year-Month	✓	✓
Journal-Year	✓	✓
Fit statistics		
Observations	1,020,091	1,020,091

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C4: Effect of press release on patent citations from PQR and non-PQR teams moderated by the use of specialized language

Dependent Variables:	Log(Patent Cites + 1)	
Model:	Non-PQR Team (1)	PQR Team (2)
Variables		
Press Release (0/1)	0.239	1.350
	(0.343)	(0.866)
% Specialized Words	-0.008	0.072**
	(0.012)	(0.030)
Press Release (0/1) × % Specialized Words	1.548***	3.548***
	(0.417)	(1.039)
N. Authors	0.000	-0.001
	(0.002)	(0.005)
N. Affiliations	-0.001***	-0.005***
	(0.000)	(0.001)
Fixed-effects		
Subfield-Year	✓	✓
Year-Month	✓	✓
Journal-Year	✓	✓
Fit statistics		
Observations	1,020,091	1,020,091

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

D Heterogeneity in Treatment Effects

Table D1 presents results for heterogeneity in the effect of press releases on patent citations across various subgroups of the data. The table is structured to explore three key dimensions of potential heterogeneity. First, Models 1-3 present results separately for different scientific disciplines, allowing for a comparison of how the impact of press releases varies across fields. Next, Models 4-6 divide the sample into three categories based on journal prestige: Low, Mid, and High. This stratification helps determine whether press releases have differential impacts for papers published in more prestigious versus less prestigious journals. Finally, Models 7-9 categorize papers based on the ranking of the last author's affiliated university. The analysis presents results for three groups: Top-20 universities, those ranked 20-50, and those ranked 50 and below. This breakdown allows for an examination of how institutional prestige interacts with the effectiveness of press releases in driving commercial applications of research.

The field-level analysis (models 1-3) reveals significant variation in the impact of press releases across different scientific disciplines. All three examined fields show positive effects, but with notable differences in magnitude. The coefficient for effect of press release is smallest for Medicine 0.553 ($p < 0.05$), followed by Biology 1.834 ($p < 0.01$). Papers in Chemistry benefit the most from press release 2.901 ($p < 0.05$). The F-statistics, which reflect the strength of the instruments in the first stage of the 2SLS, differ significantly across fields: 86 in Biology, 57 in Medicine, and only 14 in Chemistry, suggesting varying strengths of the instrumental variables used across these models.

Examining the effect of press releases across different journal ranks (models 4-6) reveals a strong and positive effect in high-ranked journals (1.600, $p < 0.01$), which diminishes for mid-ranked journals (1.559, $p < 0.05$). Intriguingly, the effect turns sharply negative in low-ranked journals (-13.153), although this result is not statistically significant ($p > 0.05$). The strength of the first stage varies substantially in these sub-samples. While the instrument is strong for high-ranked (F-Stat:164) and mid-ranked journals (F-Stat:20), the first stage relationship is weak for low-ranked journals (F-Stat:0.32). This variability may be due to the lower incidence of press releases among low-ranked journals, where only about 1% of papers are accompanied by a press release, compared to 2% in mid-ranked and 6% in high-ranked journals. Consequently, papers in low-ranked journals exhibit a low baseline rate of receiving press releases and are less susceptible to changes due to congestion at press offices.

The analysis across universities ranked in the Top 20, 20-50, and 50+ reveals that press releases significantly increase patent citations in Top 20 and 20-50 ranked university publications (2.787, $p < 0.01$ and 2.135, $p < 0.05$, respectively). The effect diminishes and becomes non-significant as we move to the Top 100 ranked universities. The corresponding F-statistics also decrease, indicating a drop in the explanatory power of the models as university rank decreases (23 for Top 20, 10 for Top 50, and 2.41 for Top 100).

Table D1: 2SLS: Effect of press release on patent citations from firms

Dependent Variable:	Log(Patent Cites+1)								
	Fields			Journal Rank			University Rank		
	Biology	Medicine	Chemistry	High	Mid	Low	Top 20	Top 50	Top 100
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Press Release (0/1)	1.834***	0.553*	2.901**	1.600***	1.559*	-13.153	2.787***	2.135*	1.009
	(0.382)	(0.308)	(1.438)	(0.275)	(0.845)	(26.601)	(0.935)	(1.190)	(2.269)
N. Authors	0.003	0.002	0.002	0.001	0.000	0.024	-0.006	-0.004	0.003
	(0.002)	(0.001)	(0.005)	(0.002)	(0.002)	(0.043)	(0.006)	(0.007)	(0.011)
N. Affiliations	-0.015***	0.000	-0.013***	-0.006***	-0.003***	0.013	-0.010***	-0.006***	-0.005
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.031)	(0.001)	(0.001)	(0.004)
Fixed-effects									
Field-Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month	✓	✓	✓	✓	✓	✓	✓	✓	✓
Journal-Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics									
Observations	766,256	1,340,606	580,450	759,629	759,604	759,579	419,409	261,699	325,995
F-test (1st stage)	86	57	14	164	20	0.32	23	10	2.41

Clustered (Year-Week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*