Strategic Scientific Disclosure:
Evidence from the Leahy-Smith America Invents Act*

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Abstract

We examine the impact of technological competition on voluntary innovation disclosure around the enactment of the Leahy-Smith America Invents Act of 2011 ("AIA"). The AIA moves the U.S. patent system from the first-to-invent to first-inventor-to-file system and induces a patent race that increases technological competition. Firms that are slow to file a patent are disadvantaged in this race. We find that firms file fewer patents in technology areas where they lag behind their peers or completely abandon the laggard domain. Additionally, sample firms strategically increase scientific publications in their lagging technology areas in an attempt to block competitors from obtaining a patent. This effect is more pronounced when there is greater inventor mobility, among firms most affected by the AIA, and those facing financial constraints. Furthermore, the effect is also stronger in patent technology classes with fewer experienced attorneys and those characterized by more intense competition. We find that peers of laggard firms experience greater patent filing rejections for novelty and obviousness reasons after the AIA, suggesting that strategic scientific disclosure is effective.

Key words: technological competition, strategic disclosure, scientific publication, patent race, America Invents Act

JEL codes: D23, M40, M41, O30, O31, O32, O34, O39

1. Introduction

The Leahy-Smith America Invents Act of 2011 ("AIA") switches the patent grant rule from the "first-to-invent" to the "first-inventor-to-file" system (Goldman [2011]). Under the "first-to-invent" system, if two entities attempt to patent the same invention, the entity with the right to receive a patent was the first to be able to document the discovery (e.g., using private laboratory notes). In contrast, for patents filed under the AIA's "first-inventor-to-file" system, the patent right is given to the inventor who files the patent application first, independent of whether she is the first inventor to discover the technology. Therefore, the AIA induces a race to the patent office by incentivizing firms to file a patent application sooner. We examine whether the AIA disadvantages firms who lag behind competitors in a given technology domain and if so, firms' strategic disclosure response.

The innovative process begins with firms investing in R&D and successful investments lead to the discovery of an invention. For firms whose technologies are best protected through patenting, the discovery phase then moves to the patent filing phase where firms draft the detailed description of the invention and enumerate the specific uses that merit patent protection. We define technological competition as the period beginning with an R&D investment and culminating in a patent filing. By creating a race to the patent office, the AIA essentially shortens the length of the competition as firms have incentives to file a patent application earlier, which intensifies technological competition (see **Figure 1**). We expect that firms lagging behind their competitors in a given technology area are disadvantaged when the finish line of the technology race is moved closer and these firms will resort to strategic disclosure to minimize losses.

Firms can pursue advancements in multiple technology areas and a firm's position relative to competitors can differ by technology area. We define a laggard patent class as technology areas where a firm's patenting activities lag behind other firms competing in the same technology space.[1] Specifically, if a firm's patent stock in a given technology area scaled by the firm's total patent stock is less than the 25th percentile of peer firms in a technology area, a firm is a laggard in that technology class. For example, in the CPC technology subclass B64C related to airplanes and helicopters, IBM is identified as a laggard given that its patent stock in this class only accounts for 0.004% of its patent portfolio, falling in the bottom quartile of firms in the subclass. In contrast, Boeing is not identified as a laggard given its patent stock in this subclass accounts for 9.4% of its total patent stock, far above the 25th percentile of its technological peers.[2]

We expect that if a firm lags behind in a patent class, it will rely less on patenting or even completely abandon this technology domain after the AIA. We find that, relative to non-laggard classes, firms file fewer patents in their laggard classes and they are also more likely to exit laggard technology domain post-AIA, suggesting firms anticipate lower future returns to patenting inventions in their laggard areas. These results validate our measure of laggard classes and demonstrate that laggard firms did change their innovation strategy as a result of the AIA.

We next examine laggards' strategic disclosure response to the AIA. Due to the nature of a patent race that rewards only a single leader, prior literature predicts a profit-maximizing strategy for the laggards of a patent race: do what they can "not to lose" (Parchomovsky [2000]). We expect pre-emptive disclosure can be an effective strategic response for laggards to achieve this goal. If a laggard can publicly disclose a sufficiently similar invention as a rival prior to the competitor being

[1] On average, our sample firms compete in nine distinct patent technology subclasses as defined by the patent classification system used by the U.S. Patent and Trademark Office ("USPTO"). We refer to a technology area where a firm lags behind competitors as a "laggard technology domain", "laggard area" or "lagging class" and firms who have at least one lagging technology area as a "laggard" or "laggard firm".

[2] Importantly, we identify laggard firms based on the size of their *patent portfolio* (i.e., patent stock) in a given area and not the firm's *overall size*, such as market cap or total assets. For example, despite IBM being a large patenting firm, IBM is actually classified as a laggard firm in the airplanes and helicopter technology area. Accordingly, even IBM can lag behind companies that predominately compete in IBM's non-core technology (i.e., airplanes). We examine the robustness of our results to alternative definitions of laggard firms in section 6.1.

safe from pre-emptive disclosure (which is the date of documented invention prior to the AIA or the patent filing date after the AIA), the patent office can reject a rival's patent application as non-novel or obvious. Pre-emptive disclosure thus raises the bar for competitors to obtain exclusive patent rights and increases the likelihood the technology will remain in the public domain, allowing the disclosing firm to use the technology without paying licensing fees. This strategy also buys laggards time to catch up in the patent race for subsequent follow-on inventions. In sum, the AIA made pre-emptive disclosure a more attractive strategy for laggards as it extended the period over which a pre-emptive disclosure can be made and effectively prevent competitors from obtaining a patent (see **Figure 2**). We examine scientific publications as a method of pre-emptive disclosure.

Scientific publications include the publication of research findings in academic journals or conference proceedings and a significant number of corporations publish their research in these scientific outlets (Arora et al. [2021], Baruffaldi et al. [2021]). Scientific publication is an appealing disclosure strategy for laggard firms given its visibility in the scientific community and the short publication timeline compared to alternatives. Survey evidence indicates that more R&D scientists rank scientific publications as an important source of information about rivals' R&D efforts than patents (Cohen et al. [2002]). In the sciences, the entire review process from submission to publication takes place in three months or less for two thirds of manuscripts and six months or less for eighty-seven to ninety-two percent of manuscripts (Huisman and Smits [2017]).[3] Given the visibility of scientific publications in the research community, publicly disclosing enabling information to competitors about ongoing R&D projects carries significant proprietary

[3] For example, the website for the highly influential journal, Nature, states "Nature makes decisions about submitted papers as rapidly as possible. All manuscripts are handled electronically throughout the consideration process. Authors are usually informed ***within a week*** if the paper is not being considered. Most referees honour their prior agreement with Nature to deliver a report **within seven days or other agreed time limit**, and send their reports online. Decisions by editors are routinely made very rapidly after receipt of reports, and Nature offers an advance online publication (AOP) service to an increasing number of manuscripts". See https://www.nature.com/nature/for-authors/editorial-criteria-and-processes.

costs, not only for a given invention, but also for the firm's larger R&D agenda. Accordingly, we do not expect all firms to uniformly increase scientific publications in all technology areas after the AIA. Instead, we expect firms lagging in a patent class to resort to scientific disclosures in the related scientific fields as a method "not to lose". In other words, we expect laggard firms to disclose more scientific publications in their laggard classes relative to two benchmarks: 1) firms that operate in the same technology area but are not lagging behind in the patent race and 2) the laggard firm's own technology classes where they do not lag behind competitors.

Our empirical analyses are based on a sample of Compustat firms from 2008 to 2015 with corporate scientific publication information from Arora et al. [2021] and for which we are able to obtain granular publication-level and patent-level characteristics. We employ a difference-in-differences (DID) design and examine whether firms increase their scientific publications in their laggard technology classes during the post-AIA period, comparing them to both non-laggard classes within the focal firm and those of peer firms. We find that firms increase scientific publications in their laggard classes after the enactment of the AIA, relative to non-laggard classes.

Next, we perform three sets of cross-sectional tests to examine variation in inventor mobility, firm characteristics, and technology class-specific variation. First, firms must have some awareness of competitor activity and their own relative position in the patent race in order to effectively use strategic scientific disclosure. Thus, we expect and find that firms that benefit from greater inventor mobility to be more informed and publish scientific articles to a greater degree. The second set of tests focus on two firm characteristics. First, because non-U.S. countries were already under first-to-file regimes throughout our entire sample period, we expect firms that also filed for patent protection in foreign jurisdictions in the pre-period were less impacted by the AIA. Consistent with this expectation, we find that the use of pre-emptive publication is stronger among firms that rely less on foreign patent protection. Second, we find that AIA-induced pre-emptive publications are concentrated among financially constrained firms, which are less able to mitigate the costs of the AIA compared to resource-rich firms. In the third set of cross-sectional tests exploring technology class variation, we find that pre-emptive disclosure is more prevalent among the subsample of patent classes with constrained access to experienced attorneys to prepare patent applications, and for classes facing greater competition.

We also perform various robustness analyses to ensure the reliability of our main results. First, we show that our main results are robust to the use of alternative measures for lagging technology areas. Second, when examining firms' strategic scientific publications in response to patent competition, we consider a scientific publication field related to a patent class if it ranks among the top three most-cited scientific fields by all patents in that class. In our additional analysis, we show that our results hold using alternative thresholds for linking a patent class to publication fields. Third, we validate the parallel trends assumption by showing that there is no change in publication in scientific fields related to laggard patent classes in the years leading up to the AIA. Fourth, to further ensure that our results are not driven by unobservable firm characteristics, we randomly assign the laggard classes within a firm. We repeat this exercise 1,000 times and find that the average coefficients are not significantly different from zero. Therefore, unobservable firm characteristics are unlikely to fully explain our results.

Finally, we explore the consequences of pre-emptive scientific publications for the disclosing firms' peers. We use data from the patent granting process to identify whether patent applications are granted or denied, and if denied, the reason for rejection. If laggards' strategic scientific disclosure is effective, we expect that their peers' patents in the related technology classes are rejected more often for lack of novelty and obviousness in the post-AIA period. We find that the percentage of peers' patent rejections related to lack of novelty and obviousness reasons increases after the implementation of the AIA relative to peers of non-laggards over the same period. This evidence suggests that laggards' strategic disclosure of scientific publications is at least partially effective in precluding peers from obtaining patent protection.

We contribute to the broader literature on strategic disclosure and to more recent work examining the effects of competition on voluntary innovation disclosure specifically. Prior studies on strategic disclosure often focus on the proprietary costs of disclosure (Dedman and Lennox, 2009; Beyer et al., 2010; Koh and Reeb, 2015; Bernard, 2016; Aobdia and Cheng, 2018). In contrast to examining the disclosure costs, our study highlights a strategic disclosure benefit that can prompt lagging firms to increase disclosure. While prior work on competition and voluntary innovation disclosure has examined competitive effects and deterrent disclosure, our study's focus on firms' pre-emptive disclosure incentives in a patent race in their lagging technology areas via scientific publications is unique (Cao et al. [2018]; Glaeser and Landsman [2021]; Zhang [2024]).

We also contribute to the emerging literature on corporate R&D disclosures through scientific publications. Scientific publications directly reveal firms' research findings to the public and serve as public goods. Despite the potential proprietary costs, firms actively publish their R&D outputs in scientific outlets. Recent literature documents some economic incentives for this arguably puzzling practice. For example, Baruffaldi et al. [2021] provide evidence that firms increase scientific publications in response to capital market demand for such information. Shen [2021], using AI-related patents and publications, shows that firms' scientific publications contribute to the reciprocity through which focal firms benefit from follow-up innovations. We show that the AIA results in laggard firms strategically increasing voluntary innovation disclosure through scientific publications, which could have implications for future knowledge spillovers.

Finally, this is one of the first papers that examine the consequence of the AIA. The AIA is the most significant patent legislation reform since 1952 (Goldman [2011]) and legal scholars have argued the AIA can weaken incentives to innovate for under resourced parties (Case [2013]). The consequences of the AIA are of substantial interest to regulators, technocrats, and academics (Abrams and Wagner [2013]). Huang et al. [2021] show an average decline in innovating firms' general R&D disclosures after the AIA, measured as the number of sentences containing R&D keywords in 10-K. They conclude that the AIA negatively impacts firms' voluntary R&D disclosure due to increased proprietary costs. Unlike general R&D disclosure, technical and detailed R&D disclosure through scientific publications function as "prior art" and can preclude competitors from patenting substantially similar technology. This paper complements Huang et al. [2021] by documenting that the AIA can have a positive effect on firms' scientific disclosures.[4]

2. Related Literature and Institutional Background

2.1 Related Literature

Recent research emphasizes the heterogeneous nature of competition, including distinguishing between product market competition and technological competition (Bloom et al. [2013], Cao et al. [2018], Glaeser and Landsman [2021]). Bloom et al. [2013] distinguish between peers in the product market versus technology peers and argue that product market competitors need not be technological competitors. Cao et al. [2018] find a negative association between the relative magnitude of product market peers' R&D to a firm's own R&D and new product

[4] Cuny et al. [2022] also exploit the AIA as a setting to examine the impact of transparency and control systems on political capture at the U.S. Patent and Trademark Office (USPTO). Though best known for changing the U.S. to a first-inventor-to-file system, the AIA also included provisions that increased the independence of the USPTO's funding by not allowing Congress to appropriate surplus patent application fees. Cuny et al. [2022] examine differences in patent grant rates and quality for firms with and without judiciary committee representation before implementation of the AIA and find that connected firms' patents are more likely to be granted even when of marginal quality. However, after the AIA, there is no difference between patent outcomes for firms with and without judiciary committee representation, suggesting that the funding changes in the AIA mitigated political capture. Our paper speaks to the strategic disclosure effects of the AIA for firms lagging in a technology race.

disclosures, which they interpret as a negative relation between product market competition and voluntary disclosure. Cao et al. [2018] create their proxy termed "technological peer pressure" by identifying peers in the product market space and measuring their technological investments (i.e., R&D expenditures) relative to a focal firm.

Glaeser and Landsman [2021] separately measure product market competition from technological competition and find that technological competition is negatively associated with voluntary innovation disclosure while product market competition leads to increased voluntary innovation disclosure. Importantly, Glaeser and Landsman [2021] proxy for innovation disclosure using the voluntary acceleration of patents that have already been filed with the USPTO — a form of disclosure that does not jeopardize the disclosing firm's ability to obtain patent protection. In contrast, scientific publications do not impart intellectual property rights and in fact are frequently included as citations in patent applications (Jaffe and de Rassenfosse [2017]), thus increasing the potential competitive costs for disclosing firms.

Zhang (2024) examines pharmaceutical companies' public disclosure of clinical trial results and finds that peer firms' R&D response depends on the competitive position of the disclosing firm. Specifically, if the disclosing firm is a leader (laggard) in the space, peer firms are less (more) likely to start new drug trials in the same area. Zhang (2024) focuses on peers' response in the clinical drug trial setting, whereas our emphasis is on the deterrent disclosure incentives of the lagging focal firm in the patent setting.

2.2 The Leahy Smith America Invents Act

The Leahy-Smith America Invents Act of 2011 is the most significant legislative change to the U.S. patent system since 1952. Among other reforms, the law switched the U.S. patent grant rule from a "first-to-invent" to a "first-inventor-to-file" system. President Obama signed the AIA into law on September 16, 2011, and the switch to the "first-inventor-to-file" system applied to patent applications filed on or after March 16, 2013.[5] Before the AIA, the patent applicant who proved to be the first inventor was granted the patent ("first-to-invent"). The U.S. Patent and Trademark Office (USPTO) determined the first inventor after an examination of evidence, including an inventor's private records. After the AIA, the inventor who first files the patent application obtains the patent, even if s/he is not the first inventor ("first-inventor-to-file").

For example, consider two biologists that investigate the same gene-editing technology. Biologist A made a breakthrough on January 1st and recorded her findings in a laboratory notebook on the same date. On March 1st, biologist B discovered the same technology and filed a patent application on April 10th. On May 10th, biologist A filed her patent application. In this fact pattern, biologist A is the one who first makes the discovery with her laboratory notebook entries as evidence, while biologist B is the one who first files the patent application. Under the "first-to-invent" regime, biologist A will be granted the patent; in contrast, under the "first-inventor-to-file" regime, biologist B will win the patent. **Figure 3** includes a timeline of this scenario.

The AIA effectively induces a race to the patent office. As illustrated in **Figure 1**, the AIA shortened the period over which firms compete for a patent on a given technology. Such a race benefits firms with patenting expertise in the area and flexibility to accelerate their patent applications, while putting firms lagging behind at a disadvantage (Abrams and Wagner [2013]).

[5] The discussions on the AIA, since its launch, centered on fairness and efficiency (Merges, [2012], Gatzemeyer [2015]). The "first-to-invent" patent system before the AIA awards the first inventor the patent, thus being a relatively fair practice. However, in practice, identifying the first inventor requires the courts to thoroughly examine all relevant records and evidence, such as the laboratory notes. A thorough examination process, together with actual interference among different parties, makes the "first-to-invent" system very costly (Pravel [1991]). The shift to "first-inventor-to-file" through the AIA improves cost efficiency at the cost of fairness.

2.3 Corporate Scientific Publication

Corporate scientific publication is a voluntary disclosure channel of firms' early-stage research efforts. Scientific publications from U.S. public firms account for a significant proportion of the public knowledge in open-source science communities (Arora et al. [2020]). For example, through 2021, IBM hired over 100 in-house scientists whose academic work received more than 10,000 citations based on Google Scholar.[6] From 2020 to 2021, IBM published 54 academic articles in physical science (tracked by Natural Index), making it one of the top 100 most research-active institutions among other prestigious academic institutions in North America. According to Elsevier (a leading publishing firm specializing in scientific content), during 2020, about 126,000 out of 560,000 academic articles (22.5%) have at least one author from the corporate sector.

The value of corporate in-house research is well documented (Bloom et al. [2020], Simeth et al. [2016]), yet the practice of publishing firms' research output in public academic journals remains arguably puzzling. Corporate scientific publications trigger knowledge spillovers and create significant proprietary costs to the publishing firm, more so than patents (Arora et al. [2021], Gans et al. [2017]). Such proprietary costs could discourage firms from publishing their research.

Prior research documents several benefits from scientific disclosure not necessarily motivated by pre-emptive disclosure. First, firms publish academic articles for their suppliers and customers. Harhoff et al. [2004] demonstrate that disclosing in-house research output to suppliers who could then use this knowledge to adapt their supplies. Corporate scientific publications can also help firms compete for product-market dominance (VanderWerf [1992], Polidoro and Theeke [2012]). Second, allowing employees to publish in academic journals is a common human resource instrument to attract and retain talent (Stern [2004], Sauermann and Roach [2014]). Shen [2021]

[6] https://scholar.google.com/citations?view_op=view_org&hl=en&org=2122379019098182280

documents that a firm's scientific publications facilitate external follow-up patents that the focal firm can build on, making the focal firm's future patents more valuable and less risky. Third, investors also demand information on firms' early-stage research output (Baruffaldi et al. [2021]).

As it relates to the AIA, the strategic use of scientific publications is a form of pre-emptive disclosure that is particularly attractive for laggards. First, when a firm realizes it is unlikely to win the patent race for a technology, or patenting the invention is not worth the costs, the firm could drop out of the patent race. Alternatively, to maintain the flexibility to commercialize the invention in the future, a firm could make the invention public knowledge through scientific publications so that a rival could not patent it and gain monopoly power (Parchomovsky [2000], Johnson [2014]). Second, disclosures by one firm raises the novelty requirement for competitors to obtain a patent, thereby extending the patent race (Bar [2006]). In this extended patent race, the lagging firm has more time and thus a better opportunity to catch up (Baker and Mezzetti [2005], Bar [2006])).

The shift from "first-to-invent" to "first-inventor-to-file" system has made pre-emptive publication a more attractive strategy for a lagging firm. As illustrated in **Figure 2,** under the "first-to-invent" system in the pre-AIA period, it is difficult for a lagging firm to prevent a leading firm from obtaining a patent by publishing interim research results given the shorter time period over which pre-emptive disclosure is effective (up to the discovery date).[7] The "first-to-file" system under AIA, by contrast, makes pre-emptive publication a more effective strategy for a lagging firm because it extends the effective strategic disclosure window all the way up to the patent filing date.

[7] Furthermore, prior to the AIA, a laggard firm could document their discovery date internally and that private record would be sufficient to obtain a patent right without a firm having to proceed further down the innovative process and make a scientific publication.

3. Hypothesis development

Proprietary costs are the key cost-based determinant of firms' R&D disclosures (Darrough and Stoughton [1990], Verrecchia [2001], Guo et al. [2004]). Such competitive costs are especially severe when disclosing early-stage research outputs, the evaluation and commercialization of which take a significant amount of time. Parchomovsky [2000] and Bar [2006] develop models of patent races that make the choice to publish scientific articles endogenous. They argue that the costs of scientific disclosure that prevent all firms, including those ahead in a patent race, from disclosing include 1) the risk of making a public disclosure that can benefit competitors but proves unnecessary to win the patent and 2) potentially raising the bar for the firm to obtain its own patent and thereby delaying the payoff from winning the race.[8]

Bar [2006] argues that firms strategically publish scientific articles when they lag rivals in the patent race and the competitor is close to obtaining a patent. Laggards have an incentive to publish the least amount possible to extend the patent race and even then, only do so when they are far enough behind. Parchomovsky [2000] highlights that laggards can benefit from pre-emptive disclosure by preventing a rival from obtaining a patent, thereby keeping the technology in the public domain without paying licensing fees. Scientific publication becomes more attractive to laggards the more likely it is that a rival will obtain a patent.

Laggards believe their competitor will beat them to the patent office when the rival has superior human resources or started earlier, greater access to financing, or the competitor places greater relative emphasis on a given research project (Parchomovsky [2000]). The model in Bar [2006] assumes that firms' progress towards obtaining a patent is common knowledge but argues

[8] The U.S. does not consider a firm's own disclosure to be prior art when considering the patentability of an invention as long as the patent filing date is one year or less before the disclosure date (35 U.S.C. 102(b)(1)(A)). However, foreign jurisdictions do not have such an exception.

that the prediction that lagging firms use strategic disclosure remains when laggards perceive the probability of the leader obtaining the patent is sufficiently high. In practice, firms can gather information about the status of competitors' research efforts through hiring their employees (Kim et al. [2021], Mehta et al. [2021]), through informal discussions among researchers (Cohen et al. [2002]), or inferring their relative position in a technology space based on competing firms' past patents (a practice known as patent landscaping, see Pargaonkar [2016]). While a firm's knowledge of competitor progress is likely imperfect, given the "winner-take-all" nature of the patent system, a firm can rationally consider strategic disclosure if the assessed probability they are behind at least one other firm is sufficiently high.

In our setting, we expect that after engaging in research, if a firm makes a discovery, it can develop the discovery into a publishable scientific publication and then further refine a discovery into a patent application (Parchomovsky [2000]).[9] The first-to-file system under the AIA, as opposed to the first-to-invent system, essentially shifts relative emphasis to the speed of filing and partially away from the speed of discovery.[10] This shift likely disadvantages firms with less expertise in a particular patent technology area.

[9] The costs of filing a patent after having made a discovery that would allow for a scientific publication include both additional scientific development and legal expertise. First, on the spectrum between "research" and "development", scientific publications fall closer to the "research" side of the spectrum, while patents lie closer to the "development" end of the continuum. While scientific publications do report details of how experiments are conducted and the results, patent applications require sufficient disclosure that "one reasonably skilled in the art could make or use the invention from the disclosures in the patent coupled with information known in the art without undue experimentation. Second, Somaya et al. [2007] point out that the assumption that "inventions generated by R&D are automatically converted into patents" is an oversimplification and that the patent filing process includes legal resources to perform a search of prior art, prepare patent applications, and subsequently navigate the application through the patent grant process.

[10] Certainly, the speed of discovery remains important in the post-AIA era. We merely contend that prior to the AIA, the speed of filing a patent application was not a determining factor in obtaining patent rights in a competitive area and that the AIA increased the importance of filing speed.

While the best strategy for the leaders of a patent race is to quickly gather resources and *win* the race, the goal for a firm trailing behind in a technology area is "not to lose".[11] Pre-emptive publication is a powerful defensive strategy a firm can employ in its lagging technology area to achieve this goal. Strategic disclosure, or pre-emptive disclosure, is the use of disclosure by a lagging firm to block the leading firm in obtaining a patent (Joachim [2015]). Because patents are evaluated in light of the prior art, disclosures by one firm make it more difficult for any other firm to claim a related patent.[12] If the laggard firm does not believe it can successfully obtain a patent related to the disclosed information given its competitive position, disclosure serves as a defensive mechanism by creating prior art that could stop rivals from obtaining the exclusive rights to use an invention, thereby excluding the laggard firm from using the technology without paying royalties.[13] Furthermore, because disclosure raises the bar for rivals to obtain a patent, scientific publications can extend the patent race for follow-on inventions the technology area, giving the disclosing firm time to catch up in the next stage of the technology race.

A discovery precedes both a scientific publication and any related patent filing. Thus, an important factor to consider is the amount and type of incremental work necessary to take a discovery from an academic publication to a patent filing.[14] For laggard firms that have already

[11] Pacheco-de-Almeida and Zemsky [2012] develop a model to explain why some innovators, particularly technology leaders, freely reveal their intellectual property. They argue that such disclosure may effectively dissuade rivals from concurrently investing in innovation. Instead, it induces rivals to wait and imitate, thereby alleviating competitive pressure. The key difference between Pacheco-de-Almeida and Zemsky [2012] and the models we rely on in our study (Parchomovsky [2000] and Bar [2006]) is that they examine free revealing as a strategy for a technology "leader" (see their page 777), while we focus on disclosure strategy of a laggard.

[12] Even if a publication does not by itself trivialize an invention may still make it unpatentable in combination with other prior art references due to non-obviousness requirement (Parchomovsky [2000]) (i.e., what is required for a scientific publication to serve as "prior art" is not as significant as a patent). All a publication needs to do is contribute the "marginal obviousness increment" to the prior art in order to preclude a patent.

[13] Keeping the invention as a trade secret is another option. However, in competitive areas, if a firm holds their innovation as a trade secret, a competitor who independently discovers the same invention could patent essentially the same idea, thus blocking the focal firm from using the invention, or later file a patent infringement case.

[14] The seven-step new product development process outlined in Case (2013) suggests that there is indeed additional technological development after the point at which a scientific publication is made, but before a patent is filed. The first step is research, which involves scientists and engineers and includes academic publication in her framework.

made a discovery that can be published in a scientific article, there is some benefit to additional technology development to expand the legal claims and strengthen the resultant patent rights. But if the technology is sufficiently developed to successfully pre-empt competitors receiving a patent, we expect legal expertise and legal costs to be a primary drive of why firms choose to publish scientific articles in lieu of filing a patent when they lag behind in a technology area.

The above discussion suggests firms lagging in a technology domain are more likely to benefit from scientific publication after the AIA. As discussed in Section 2, the AIA increases the effectiveness of a pre-emptive publication strategy for a laggard. This leads to our hypothesis:

H1: *Firms are more likely to increase scientific publications in a laggard technology class than a non-laggard class in response to an increase in technological competition.*

Approximately 62% of scientists working in R&D labs in the U.S. indicate that publications are a moderately or very important source of information on competitors' R&D efforts, more than patents (49%) or informal exchange (51%) (Cohen et al. [2002]). Given the proprietary cost of revealing enabling information to competitors about an ongoing R&D agenda, we do not expect all firms to uniformly increase scientific publications after the AIA. Instead, we expect laggard firms to resort to scientific disclosures more often in their lagging technology class(es) as a method "not to lose" than firms leading the patent race whose optimal strategy is to "win" the patent race.

Steps two and three are technology characterization and conceptualization, which primarily involve scientists and designers, but may also involve intellectual property lawyers. Subsequent steps prove the concept and produce a prototype (steps four and five). It is not until step six in the development process that commercial designs are made, a patent application is filed, and marketing development begins (collectively step six) before the process culminates in a product launch (step seven).

4. Research Design

4.1 Data and Sample Selection

We begin with a sample of Compustat firm-years from 2008 to 2010 and 2013 to 2015, omitting the years between the AIA announcement date and its effective date (2011 and 2012) to remove any anticipatory effects from our analysis. We require firms to have non-missing scientific publication information from Arora et al. [2021], to have at least one scientific publication during our sample period, and to not be in the financial industry (SIC 6000-6999). As Arora et al. [2021] only include a variable to count the total number of scientific publications in a firm-year, we then perform extensive procedures to match firms to individual scientific publications so we can identify the technology area to which their research pertains. Ultimately, we employ a sample of 821 firms that operate in 462 patent classes and 120 scientific publication fields. Our final sample includes 1,868,790 firm-year-patent class observations. Please see the Online Appendix for further details regarding the data and sample selection procedures.

4.2 Key Measure for Laggard Class and Summary Statistics

We seek to capture whether a firm's on-going R&D projects are in technology spaces where the firm leads or lags its competition. Our first step is to define firms' laggard status at each patent technological class level for a given year. We use patent filings to proxy for the technology area and progress of a firm's on-going R&D projects and measure its leading or laggard status in a technology class based on its cumulative patent stock. We consider a firm to be a laggard in patent technology class *j* in a given year *t* if the firm's cumulative patent stock in this class, scaled by its total cumulative patent stock in all classes, falls within the bottom quartile of all the firms that file a patent in class *j* in year *t*. Patent stock is defined as the sum of all patents *p* filed from year t-20 to year t-1 by firm *i* for each technology class *j*. The expectation is that firms frequently patenting in a cluster of related technologies are able to quickly file patent applications, but that firms are less adept at preparing applications in technology areas where the firm has less relative experience (Somaya et al. [2007]). We follow prior literature and use a perpetual inventory method with a 15% annual depreciation rate to calculate patent stock (Bloom et al. [2013], Cao et al. [2022]).[15] Importantly, a firm must be actively competing in a technology class in order to publish scientific findings in that technology space. To ensure that a firm has not completely exited patent class *j*, we also require that the firm has at least filed one patent for the patent class in the current year.[16]

Figure 4 provides an illustrative example of the *Laggard* class definition. Firm 1 is currently filing patents in two patent classes: A and B. Firm 1's cumulative patent stock in technology class A and B is 9 and 1, respectively. We then scale the firm's patent stock by the total number of patents (10), such that firm 1's relative patent percentage for class A and B is 90% and 10%, respectively. Since firm 1's relative patent percentage of 10% is lower than the 25th percentile of its tech-peers in class B (20%), firm 1 is a laggard in technology class B. In contrast, firm 2's relative patent percentage in class A of 25% is lower than the twenty-fifth percentile of its tech-peers (30%). However, we do not consider firm 2 a laggard in this class because it does not actively file patents in this technology area (i.e., there are zero patent filings in Class A in year *t*), suggesting firm 2 might have discontinued R&D in this space. Finally, firm 3 only actively files patents in class B and its stock of patents in class B of 100% is above the 25th percentile, thus firm 3 is not a laggard in class B. We define the treatment variable *Laggard_pre* that takes on the value of one for a firm-patent class if the firm is a *Laggard* in this patent class in any of the three pre-

[15] Specifically, we calculate a firm's patent stock for the past 20 years assuming a decay rate of 15% as follows: $PatentStock_{i,t} = \sum_{n=1}^{20}(1-15\%)^{n-1} \times \#Patentfiling_{i,t-n}$.
[16] Our results are robust to various alternative measurement choices for defining *Laggard* (see section 6.1).

AIA years (i.e., 2008-2010). Using a consistent definition of treated firm-patent classes ensures that treatment status does not change for a given firm-patent class over our sample period, facilitating our DID analysis.

Table 1 Panel A presents the summary statistics on the publication and patenting activities by our sample firms. On average, our sample firms publish approximately 38 scientific papers in 9 scientific fields each year. The average number of publications over our sample period is comparable to Arora et al. [2021]. Our sample firms tend to have diverse research portfolios. They compete in 8.18 different patent classes, 1.86 of which are defined as laggard classes. In addition, firms in our sample file patents in approximately 30 different classes from 1991 to 2010, with the maximum being 336 classes (untabulated), suggesting the technological classes firms compete evolve over time. On average, our sample firms have 4.48 classes in which they were considered as a laggard in at least one of the 3 years in pre-AIA period. For context, on average, firms patent in 13.51 classes in the 3 years of the pre-AIA period, suggesting that approximately one third of tech classes are lagging classes.

Panel B shows that, compared to the Compustat universe, our sample firms tend to be larger, more R&D intensive, less tangible, less levered and less profitable. **Table 2** presents a Pearson correlation matrix. The correlations show that our treatment variable of interest, *Laggard_pre*, is positively correlated with scientific publications, *Pub*, providing univariate evidence that firms publish more scientific articles in technology areas where they lag behind peers. Our next tests examine this association in a multivariate context and explicitly examine the impact of the AIA.

4.3 Regression Model

4.3.1 The Differential Impact of the AIA on Laggard Classes

To validate that the AIA differentially affects firms' patenting activities in laggard versus non-laggard technology domains, we estimate the following regression at the firm-year-patent class level:

Eq. (*1*):

$$Innovation_{i,j,t} = \beta_1 Laggard\_pre_{i,j} \times Post_t + Firm \times Year\ FE + Firm \times TechClass\ FE + TechClass \times Year\ FE + \epsilon_{i,j,t}$$

For firm *i*, patent class *j*, year *t*, the dependent variable in Eq. 1 can be one of two variables: 1) the number of patent applications (*Patent*), and 2) an indicator for exiting a patent technology space (*Exit*). The variable of interest is the interaction between $Laggard\_pre_{i,j}$ and $Post_t$. $Post_t$ is an indicator variable that equals one if the firm-year observation is during the 2013 to 2015 post-AIA period, and zero for firm-years from 2008 to 2010. $Laggard\_pre_{i,j}$ is one if firm *i* patent class *j* was identified as a laggard class in any of the three years during the pre-AIA period, and zero otherwise.

In all our main analyses, we control for firm×year, firm×techclass and techclass×year fixed effects. In Eq. 1, our fixed effect structure orthogonalizes our measure of patenting activity relative to the average for the firm-year, firm-technology class, and technology-class year, allowing our coefficients to capture the effect of within firm year, firm-patent class, and technology class-year variation on firm patenting decisions.

4.3.2 Pre-emptive Publication by Laggard Firms

To test our main hypothesis, we adopt a DID design to compare changes in scientific publications by treated (laggard) and control (non-laggard) firm-year-patent classes before and after the enactment of the AIA. Specifically, we estimate the following regression model:

Eq. ***(2):***

$$Pub_{i,j,t} = \beta_1 Laggard\_pre_{i,j} \times Post_t + Firm \times Year\ FE + Firm \times TechClass\ FE + TechClass \times Year\ FE + \epsilon_{i,j,t}$$

where $Pub_{i,j,t}$ is the natural logarithm of the total number of scientific publications for firm *i* in the top three scientific fields related to patent class j in year t. $Post_t$ and $Laggard\_pre_{i,j}$ are as previously defined. If a firm publishes more scientific articles for technology areas in which they are losing the patent race, we expect β_1 to be positive. Again, we control for firm × year, firm×techclass and techclass×year fixed effects. Our fixed effect structure allows β_1 to capture changes in a firm's scientific publication behavior for a lagging technology class relative to the scientific publications a firm makes in other technology classes that year, incremental to the average level of scientific publications a firm makes over the sample for that class and any trends in scientific publications particular to technology class in that year.

5. Empirical Results

5.1 The impact of the AIA on laggard classes' patenting behavior

Table 3 presents the results of estimating Eq. 1 where *Patent* is the dependent variable (**Panel A**) and where *Exit* is the dependent variable (**Panel B**). We find that the coefficient on $Laggard\_pre \times Post$ is significantly negative when *Patent* is the dependent variables, while it is positive when *Exit* is the dependent variables. This finding is consistent across specifications in columns (1) to (6) when we incrementally vary the fixed effect structure and is relatively stable in magnitude.[17] Collectively, these results suggest that firms reduce their patenting activity in lagging

[17] The main effect of *Laggard_pre* is significantly positive when *Patent* is the dependent variable. We require a firm-year-technology class to have at least one patent filing during the pre-period to be defined as a laggard (i.e., *Laggard_pre* equals one). This requirement ensures firms have not entirely exited that technology area. Thus, when we compare these observations with non-zero patent filings to control observations that do not have patents in that technology area, the main effect of *Laggard_pre* is positive. Similar reasoning applies for the negative main effect of *Laggard_pre* when *Exit* is the dependent variable. Including these control observations allows for firms to change

technology spaces, or even completely abandon trailing domains, in anticipation of lower returns to patenting in the post-AIA period. These results validate the definition of *Laggard_pre* as our treatment variable of interest by demonstrating that treatment firm-technology classes have been differentially affected by the AIA.

5.2 Baseline Results (H1)

Table 4 presents the results for H1. Columns (1) to (5) present results without fixed effects and with different combination of fixed effects, respectively; Column (6) presents the estimation results of Eq. 2 including firm-year and firm-technology class and technology class-year fixed effects. Across all six columns, the coefficients on *Laggard_pre*×*Post* are positive and significant at less than the 5% level. Consistent with H1, the results suggest that firms increase their scientific publications in lagging technology areas in response to the enhanced technological competition induced by the AIA. The magnitude of the coefficient (0.025) suggests that our sample firms increase their scientific publications in their laggard class by 2.5% after the AIA, relative to non-laggard classes.

5.3 Cross-sectional Variation in the Impact of the AIA on Scientific Publications

5.3.1 Inventor Mobility

As discussed in Section 3, firms must have some understanding of where they are relative to competitors in a technology race in order to effectively use strategic scientific disclosure. We therefore expect our main findings to be more pronounced when there is greater inventor mobility between firms, thereby facilitating knowledge flows among competitors. First, we exploit variation at the state level in the adoption or rejection of the inevitable disclosure doctrine (IDD) that affects

their technology areas over the sample and facilitates the inclusion of high dimension fixed effects. See further discussion in the Online Appendix.

the ability of employees with trade secrecy information to be employed by competitors (Kim et al. [2021] and Mehta et al. [2021]). Specifically, we expect firms with greater exposure to states that adopted the IDD doctrine to have less ability to learn about competitor R&D efforts. Empirically, we proxy for a firm's exposure to IDD states using the percentage of states where a firm's R&D offices locate (as measured by the location of inventors) that adopt the IDD. **Table 5** columns 1 and 2 presents the results. The findings are consistent with firms with less exposure to IDD states (i.e., firms who can more readily hire their competitors' employees) employing strategic scientific disclosure to a greater extent than other firms. Second, we proxy for inventor mobility using actual inventor movement between firms as observed in patent filing data. We measure inventor mobility in a specific technology class by the percentage of inventors that work for more than one company over our sample period. **Table 5** columns 3 and 4 show that strategic scientific disclosure is used to a greater extent when inventor mobility is high, consistent with expectations.

5.3.2 Foreign Patent Protection and Financial Constraints

We expect that our main finding is concentrated among 1) firms that rely less on foreign patent protection and 2) firms with financial constraints, respectively. First, the AIA is a U.S. patent law change that impacted how patents filed with the U.S. Patent and Trademark Office are granted. However, if a multinational firm seeks to protect its invention in multiple countries, it must file for patent protection in each country and the laws in that jurisdiction apply. All foreign jurisdictions were already under the first-to-file patenting regime prior to the implementation of the AIA in the U.S. and thus, the AIA likely did not impact firms that prioritize foreign patent protection as much as firms that focus on U.S. domestic patent protection.[18]

[18] Furthermore, a scientific publication is considered "prior art" and precludes rivals from obtaining a patent for the published technology. In many other countries, patent law considers a firm's own disclosure to be "prior art" that negates the disclosing firm's ability to obtain a patent, although there is a 12-month grace period for the disclosing firm in the U.S. Thus, pre-emptive publication is less appealing for firms if foreign patent protection is important.

We define the relative importance of foreign patent protection in two ways. First, firms that file for patent protection in foreign countries in the pre-period have demonstrated that foreign patent protection is important to their strategy than firms that never file for foreign patent protection ("Foreign Family"). Second, firms that first file for foreign patent protection and only then seek US patent protection value foreign intellectual property rights more than a firm that first files for patent protection in the US ("Foreign Priority").

Using these definitions, we split the sample into "*Local patent*" firms for whom foreign patent protection is less important and "*Foreign* patent" firms. We then estimate Eq. 2 within each sub-sample and report the results in **Panel A** of **Table 6**. Across these two different ways to capture the importance of foreign patent protection, our results are stronger in the sub-sample of firms most affected by the AIA, namely those who rely primarily on U.S. patent protection.

Second, we expect financially constrained firms to be affected by the AIA more than less constrained firms. Financial resources can be essential in the patent process. The patent filing fee structure is typically complex, including various fees such as application filing fees, patent search fees, and etc., but it is estimated that in January 2022 the average cost of a utility patent was over $50,000 (Krajec [2022]).[19] Considering any additional fees paid to foreign offices, a company that competes and file patents in multiple technology spaces can spend hundreds of thousands annually in building/maintaining its patent portfolio. Above and beyond the initial costs to file for patent protection, companies with patents must budget resources to maintain and enforce the patent over a patent's life. In 2020, the American Intellectual Property Lawyer's Association (AIPLA) reports that "in 2020, for less than $1M at risk, the trial will cost $700,000, while the very high value cases will cost $4M or more."[20] The cost of patent protection alone may be prohibitive to financially

[19] https://www.uspto.gov/learning-and-resources/fees-and-payment/uspto-fee-schedule#Patent%20Fees
[20] https://finance.yahoo.com/news/current-patent-litigation-costs-between-120200165.html

constrained firms. For example, in a study of software start-ups, Berberich [2013] shows that costs of patent filing and protection account for 64% of the start-ups' choices not to file a patent.

It is possible that resource-rich firms can overcome some of the effects of lagging in the patent race by deploying alternative resources. For example, hiring an external legal firm to prepare patent applications could effectively substitute for firm-specific expertise in patent filings (Somaya et al. [2007]). We expect that financially constrained firms are less willing or able to expend additional resources on innovative investments in which the firm is lagging.

We measure financial constraints using the leverage ratio and debt-to-cash ratio. We then split the sample based on whether the firm-level average of the financial constraint measure during the pre-AIA period is above the sample median. Within each sub-sample, we estimate Eq. 2 separately. Results are reported in **Panel B** of **Table 6**. Consistent with our expectations, the effect of the AIA on firms' scientific publications concentrates among firms with greater financial constraints. Regarding economic magnitude, laggard firms with high financial constraints (Columns 2 and 4) increase scientific publications by 2.8% and 3.5%, whereas unconstrained firms do not significantly change scientific publications after the AIA.

5.3.3 Access to Legal Expertise and Barriers to Entry

We next examine sources of variation at the technology class level to complement the prior tests using primarily firm-level variation. We expect that increases in defensive publication around AIA is concentrated in technology areas 1) lacking access to experienced attorneys and 2) facing more intense competition. First, we expect that constraints on access to legal expertise within a technology area disadvantages firms during a patent race after the AIA. Patent law is a complex and specialized filed, and obtaining a patent involves navigating various legal requirements. A patent attorney can more readily assess the patentability of an invention by conducting a thorough search of existing patents and technical literature (i.e., prior art) than someone less experienced. Furthermore, an experienced patent attorney is essential in drafting the patent. A skilled patent attorney that knows the technology area can draft precise, clear legal claims that offer the broadest protection possible without being overly vague. When there are fewer experienced attorneys in a technology area, we expect laggard firms to be more likely to give up patenting and resort to defensive publication.

We measure access to legal expertise by the ratio of the number of unique attorneys filing patent applications in technology class *j* from 1991 to 2010 to the number of patents filed for patent class *j* over the same time period. This measure captures the supply of attorneys with experience in a given technology area available to firms pursuing inventions in that domain. We partition our sample based on our sample median for this measure and **Table 7 Panel A** presents the results. The results show that the effect of AIA on pre-emptive publication is more pronounced among firms with less access to attorneys experienced in their lagging technology classes.[21]

Second, we expect firms lagging in technology areas with more intense competition to utilize pre-emptive publications to a greater extent. For instance, certain technology sectors may be dominated by a select few major players. These established companies often have a wealth of technological expertise and intellectual property, creating a barrier for new entrants who may need time to catch up (Cockburn and MacGarvie [2010]). This challenge is particularly acute within the patent system, which operates under a "winner-takes-all" paradigm. Therefore, firms trailing in technology domains that face greater competition are more likely to resort to defensive publication.

[21] We measure access to experienced attorneys at the technology class level rather than firm level because the attorney information is only available ex-post from granted patents and our laggard firm-classes, by definition, have fewer patents in the past. Therefore, measuring the *supply* of experienced attorneys at the technology class level is more exogenous to firms' choices of patenting in given technology areas.

We measure competition within a patent class in two ways: 1) the percentage patents filed by the top three most active companies in a given technology class from 1991 to 2010 (*Concentration*); and 2) the number of companies filling patents in each patent class from 1991 to 2010 (*#Competitors*). The idea is that competition increases with the dominance of leaders in a given patent class and also with the number of players competing in that technology space. The results for this sub-sample analysis are presented in **Table 7 Panel B**. Our main finding on pre-emptive publication is more pronounced when our sample firms compete in a more competitive technology domain.

6. Additional analysis and robustness tests

6.1 Alternative measures for laggard and alternative methods of linking publication fields to patent classes

We assess the robustness of our results to the use of alternative definitions of a laggard technology class. We employ three alternative measures: (1) Our main proxy considers a firm a laggard in patent technology class *j* if the firm's patent stock in class *j* as a percentage of the firm's total patent stock in all USPTO (CPC) patent classes is below the 25th percentile of its technology peers. Conceptually, this measure captures a firm's relative expertise across technology areas within the firm, rather than the total number of patents filed in an area. Alternatively, we define a laggard class based on comparing the total number of patents the focal firm files in a given technology class relative to the 25th percentile of its peers' total number of patents. (2) Our main definition of laggard is based on patent count, without considering the heterogeneity in the importance of the individual patents. In this alternative approach, we aggregate a firm's patent stock in each technology class by weighting each patent with its commercial values, from Kogan et al. [2017]. In alternative (3), we replace the commercial value with the number of future citations each patent receives, thus weighting patents by their scientific value as recognized in subsequent research. **Table 8 Panel A** reports the results of this exercise. The results employing these alternative definitions of laggard are consistent with our main results.[22]

When establishing the link between patent technology class and scientific publication field, we assume that a patent class is linked to only the top three scientific publication fields cited by all patents within that class. In **Table 8 Panel B**, we explore the robustness of our results to alternative thresholds in creating this link. Specifically, we consider retaining either the top one or five most-cited publication fields for each patent class. In a third alternative, we retain all scientific publication fields as long as it accounts for at least 5% of the total citations made by all patents in a given patent class. Our main results remain robust to all three alternative specifications.

6.2 Parallel Trends and randomization test

To provide further evidence that the change in scientific publications is attributable to the implementation of the AIA, in this section, we examine the parallel trends assumption of the DID design. The parallel trends assumption requires that the difference between the treatment group and the control group (i.e., laggard vs. non-laggard firm-patent classes) is constant in the pre-AIA period and would have continued if not for the event. Although inherently the assertion that parallel trends would have continued absent the treatment is untestable as we cannot observe the counterfactual, we are not aware of any concurrent macroeconomic events that would have

[22] We also consider the case where a firm could make a rapid entry into a new technology class by devoting significant resources. In such cases, although the firm may have a low patent stock that technology class thus be categorized as a laggard according to our measure, the firm may not necessarily be trailing behind competitors. In an untabulated analysis, we redefine *Laggard_pre* to exclude firm-patent classes with increasing patent filings in at least two out of the three pre-AIA years (i.e., 2008-2010) and exclude these growth entrant technology classes from our sample. This additional criterion drops about 14% of the *Laggard_pre* group, which then becomes part of our control group. Using this alterative definition of *Laggard_pre*, our main result remains inferentially similar. Specifically, the coefficient on *Laggard_prexPost* in column (6) of Table 4 change from 0.0252 to 0.0253 and remains significant at the 1% level. Thus, our results are robust to growth entrant firm-technology classes from the treatment group, suggesting these observations are not representative of the average treatment unit.

interacted with the implementation of the AIA in a way that would increase scientific publications for laggard but not other firm-patent classes.[23] We then assess the pre-period trends for our treatment and control (i.e., laggard vs. non-laggard) firm-technology classes.

To verify the parallel trends in the pre-AIA period, we follow prior literature and estimate the following regression:

Eq. (3):

$$
\begin{aligned}
Pub_{i,j,t} = {} & \beta_1 Y08 \times Laggard\_pre_{i,j} + \beta_2 Y09 \times Laggard\_pre_{i,j} + \beta_3 Y13 \times Laggard\_pre_{i,j} \\
& + \beta_4 Y14 \times Laggard\_pre_{i,j} + \beta_5 Y15 \times Laggard\_pre_{i,j} + Firm \times Year\ FE \\
& + Firm \times TechClass\ FE + TechClass \times Year\ FE + \epsilon_{i,t}
\end{aligned}
$$

where the indicator variables *Y08* to *Y15* represent the fiscal years 2008 to 2015, respectively. β_1 to β_5 capture the differential scientific publications of treated firm-patent classes in each of the years 2008 to 2015, with 2010 serving as the benchmark. We include the same set of fixed effects as in Eq. 2. The coefficients and 95% confidence intervals are plotted in **Figure 5**. The coefficients on $Y08 \times Treat$ and $Y09 \times Treat$ are not significantly different from zero, consistent with parallel pre-period trends.

Next, we conduct a falsification test to further validate that our findings are not influenced by unobservable firm characteristics. In this process, we randomly reassign the laggard classes within each treatment firm. If unmodeled firm characteristics drive our results, we would expect

[23] The Patent Pilot Program (PPP) in 2011 was a pilot program introduced by Congress to allow more experienced judges to hear patent litigation cases, rather than pure random assignment of judges to cases. Kim et al. [2023] use the PPP as a setting and find an increase in affected firms' patent filings, which they interpret an improvement in judicial efficiency increasing firms' incentive to innovate. We expect that any concurrent impact of the PPP in our setting is likely minimal for two reasons. First, it is unclear why the PPP would produce a change in scientific publications specifically in the technology area in which a firm is lagging its competitors. Second, we find that laggard firms *decrease* the number of patent filings after the AIA was implemented in 2013. Third, even though Kim et al. [2023] find a lagged effect of the PPP that coincides with our post period (i.e., the increase they observe begins in 2013 on average), they exploit variation in the extent to which firms were treated by the PPP based on their headquarter state. In contrast, we expect and find that laggard firms to respond to the AIA without regard to where a firm is headquartered.

to find similar results with these randomized laggard classes within a firm. Specifically, we shuffle the laggard classes within each firm and estimate Eq. 2. We repeat this exercise 1,000 times and report the average β_1. **Table 8 Panel C** reports the results. The coefficients based on the randomly assigned sample are not significantly different from zero, while they differ statistically and economically from the results using the actual data. Overall, these results help rule out alternative explanations driving our results.

6.3 Effectiveness of Strategic Scientific Publications post-AIA

In this section, we investigate the effectiveness of strategic scientific publications by examining the patent rejection consequences of the AIA for the disclosing firms' peers. Ultimately, patent grants represent a successful R&D investment that is deemed novel and nonobvious by the patent office. The number of patent grants are a function of 1) whether the patent office determines the invention meets the novelty and non-obviousness criteria given the prior art (35 U.S.C sections 102 and 103)[24] and 2) the number of patent applications the firm makes. If the patent office determines that a patent application is not novel (or is obvious) given prior disclosures, including scientific publications, we expect to observe more patent applications by laggards' peers rejected for lack of novelty or for obviousness in light of prior art. To empirically examine the impact of scientific publications for the disclosing firms' peers, we estimate the following regression:

Eq. (*4*):

$$\begin{aligned} ReasonRej\_Peer_{i,j,t} &= \beta_1 Laggard\_pre_{i,j} \times Post_t + Firm \times Year\ FE + Firm \times TechClass\ FE \\ &+ TechClass \times Year\ FE + \epsilon_{i,j,t} \end{aligned}$$

[24] A patent is deemed to lack novelty if a patent examiner can point to a single piece of prior art that already claimed each element of the technology being considered (see the Manual of Patent Examining Procedure section 2131). A patent is rejected for being obvious if "the claimed invention would have been obvious to one of ordinary skill in the art after consideration of all the facts" (see the Manual of Patent Examining Procedure section 2141), which includes consideration of multiple pieces of prior art as well as the fundamental understanding common to the technology area.

For estimating Eq. 4, we examine rejections of patent applications in each patent class *j* from applicants excluding focal firm *i*. The dependent variable in Eq. 4 is either (1) %*NoveltyRej*: the percentage of patent rejections due to lack of novelty in patent class *j* from applicants other than focal firm *i;* or (2) *%ObviousRej*: the percentage patent rejections due to obviousness reasons in scientific field *j* from peers of focal firm *i*. The variable of interest is the interaction between *Laggard_pre* and *Post*. We include firm×year and firm×technology class fixed effects. We do not include technology class × year fixed effects because the object of interest is the variation in peers' patent filings in a technology class-year. We further include the number of overall patent application filed in patent class *j* for year *t* to control for the overall level of patent applications.

Table 9 report the results. We find the coefficients on the interaction term to be positive and significant, suggesting that peer firms are more likely to receive rejections by the patent office for lack of novelty and obviousness reasons after AIA.[25] Taken together, our evidence is consistent with firms increasingly using scientific publications to deter competitors from patenting an invention post-AIA in their lagging technology classes, and that this strategy is at least partially effective.[26]

[25] A potential concern is that the observed increase in patent rejection rates after the AIA is due to technology areas that had higher ex ante patent competition that prompted higher rejection rates. If technology areas with greater ex ante competition also have a higher share of firm-technology classes defined as lagging classes, we could observe this empirical pattern absent scientific publications. We believe this is unlikely to be the case because we define a firm-technology class as a lagging class on a relative basis using the 25th percentile as a threshold. Thus, it is not the case that lagging firm-technology classes have higher ex ante competition by construction.

[26] Given that patent rejection rates increase for peer firms' non-laggard technology areas, one might expect that peers respond to mitigate those costs. We interpret the results in Table 9 as reflecting the transition period to what will ultimately be a game-theoretic equilibrium. In the immediate post-implementation period, it appears that non-laggard firms expect they can still win the race to the patent office even understanding the potential for strategic scientific disclosure or that non-laggards fail to fully anticipate the implications of the strategic disclosure strategy. However, as non-laggards observe the increased patent rejection rate after the implementation of the AIA, we do expect firms to adjust to the new equilibrium. Such an equilibrium could include increasing acquisitions or R&D to increase their speed of discovery (thereby narrowing the effective window of strategic scientific publications) or resorting to strategic scientific publication themselves despite the attendant costs. We leave the testing of these conjectures to future research.

7. Conclusion

The first-to-file system under the Leahy-Smith America Invents Act of 2011 induces a race to the patent office. We find that the AIA has an overall adverse impact on firms' patenting activity in technology classes whey they were already trailing in the race. We predict and find that affected firms strategically increase their scientific publications in academic journals after the enactment of the AIA in the very technology areas in which they lag behind as a strategy to raise the patentability threshold for rivals in the accelerated patent race. The intuition is that if a firm is less likely to successfully obtain patent rights for itself, having an invention in the public domain is preferable to having the invention in the hands of a competitor that can enforce exclusivity rights.

In cross-sectional analyses, we show that our results are more pronounced when there is greater inventor mobility, as this facilitates laggard firms in assessing their relative position during a patent race. Additionally, the effect of the AIA on pre-emptive publication among our sample firms manifests in the sub-sample of firms expected to be affected by the AIA to a greater extent: those that rely more on U.S. patent protection and those that operate with financial constraints. Furthermore, we find that firms increase their usage of scientific publications in their lagging technology areas if the firm lacks access to attorneys with experience specifically in their lagging classes or in the presence of more intense competition in that area.

One potential concern with our results is that fundamental differences between laggard and non-laggard firm-patent classes bring about the observed changes in their scientific publications around the AIA. Our main design compares technology classes within a firm year and thus uses the firm as its own control. We employ a DID design and assess the reasonableness of the parallel trends assumption at the firm-year-patent class level. Moreover, we partition our sample based on the expected impact of the AIA and our various cross-sectional tests raise the hurdle for an alternative explanation.

Overall, this paper presents consistent evidence that technological competition is an important determinant of corporate scientific publications. Scientific publications are of increasing interest to researchers as they convey early signals of firms' growth potential and innovation. Academic publications also play a unique role in the knowledge-based economy, such as the contribution to reciprocity (Shen [2021]). By accelerating the race to the patent office, our evidence shows that the AIA significantly increased corporate scientific publications. One implication of our findings that we leave to subsequent research is the potential for social welfare gains due to the increased scientific publications from firms lagging in some technology domains.

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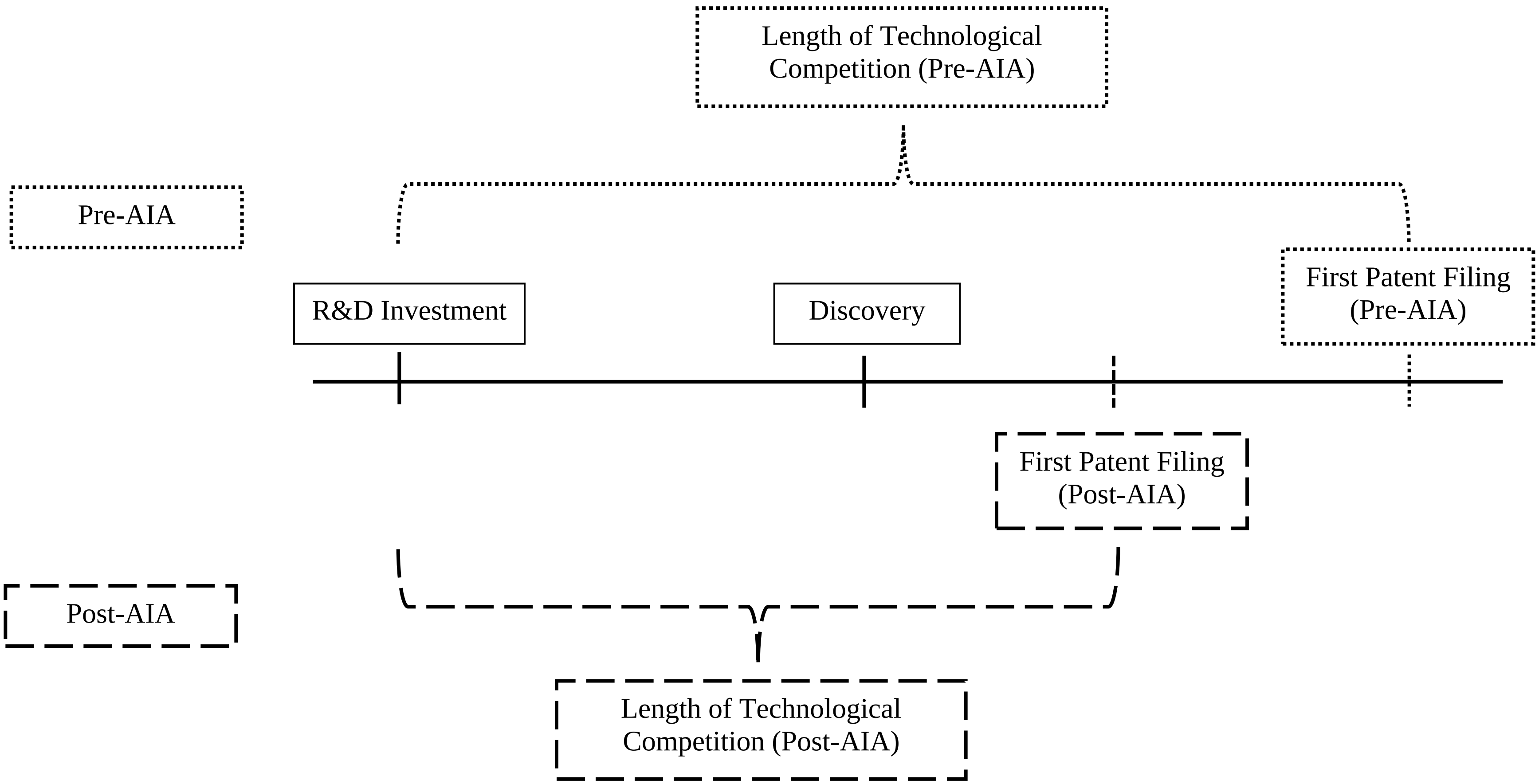
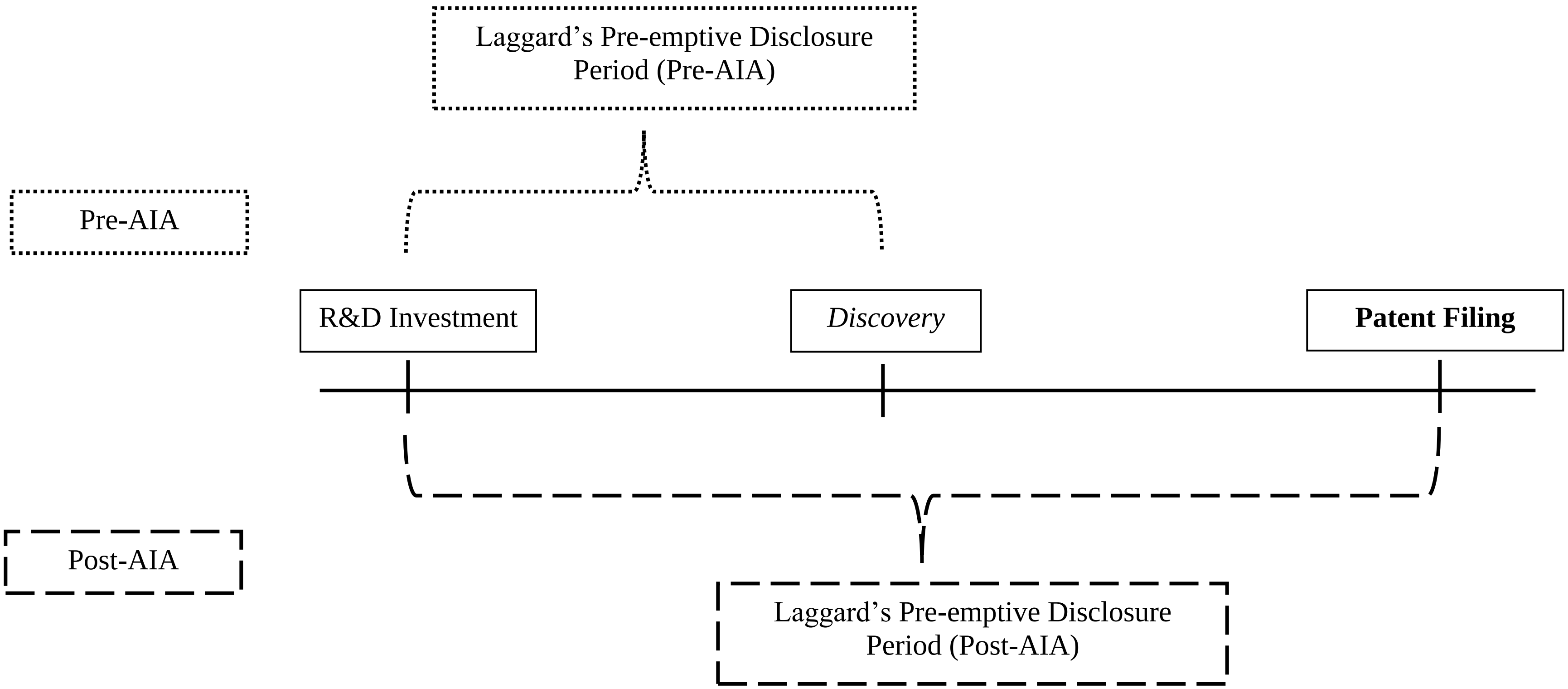
Figure 1: The Innovative Process and Technological Competition



Pre-AIA: Firms can document their discovery in lab notes and the first inventor to discover the technology obtains the patent right.

Post-AIA: The first inventor to file a patent application is awarded the patent right, incentivizing firms to file a patent application more promptly after discovery in an effort to secure patent rights.

Figure 2: The Leader's Innovative Process and the Laggard's Strategic Disclosure Response



Pre-AIA: to prevent a leader from obtaining a patent, a laggard must publish scientific findings (i.e., pre-emptive disclosure) before the leader's scientific *discovery* (e.g., documented by lab notes).

Post-AIA: a laggard can effectively use pre-emptive publication to prevent a leader from obtaining a patent up to the **patent filing** date of the leader.

Figure 3: First-to-invent vs. First-inventor-to-file

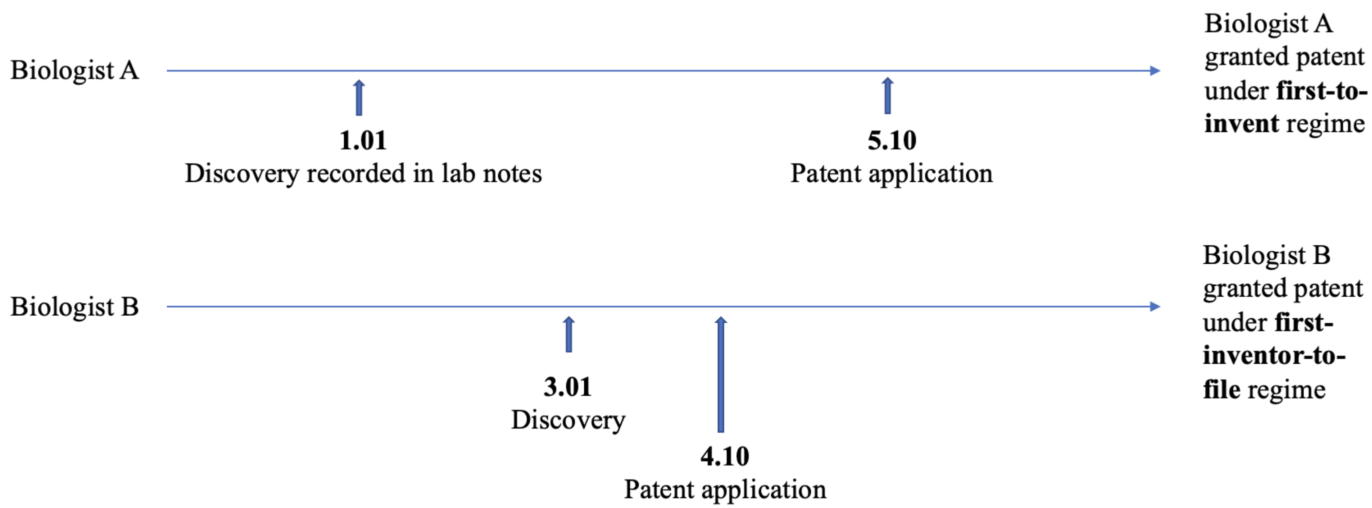


Figure 4. Illustration of Laggard Definition

	Class A				Class B			
	Firm's # of Patent filings in year t	Firm's *Patent_stock* (t-20 to t-1)	Tech Class 25th percentile *Patent_stock*	***Laggard class***	Firm's # of Patent filings in year t	Firm's *Patent_stock* (t-20 to t-1)	Tech Class 25th percentile *Patent_stock*	***Laggard class***
Firm 1	1	9 (90%)	30%	**0**	1	1 (10%)	20%	**1**
Firm 2	0	1 (25%)	30%	**0**	1	3 (75%)	20%	**0**
Firm 3	0	0 (0%)	30%	**0**	1	5 (100%)	20%	**0**

Figure 5. Parallel Trend Analysis

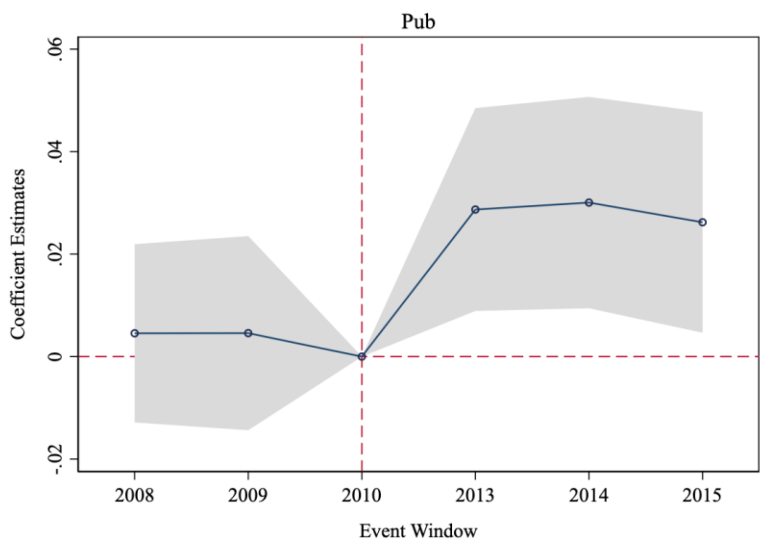


Table 1: Descriptive Statistics

Panel A: Summary Statistics of Patents, Publications, and Laggard Classes

VARIABLES	N	Mean	SD	P25	Median	P75
Annual number of scientific publications	4,079	37.928	135.659	0	4	18
Annual number of scientific fields in which a firm publishes papers	4,079	8.720	15.931	0	3	9
Annual number of patents	4,079	67.972	325.562	1	5	27
Annual number of technological classes in which a firm files patents	4,079	8.184	17.680	1	3	8
Annual number of technological classes in which a firm is a laggard	4,079	1.860	5.322	0	0	1
N of technological classes in which a firm files patents from 1991 to 2010	4,079	29.914	46.728	4	12	33
N of technological classes in which a firm files patents from 2008 to 2010	4,079	13.507	25.385	2	5	14
N of technological classes defined as *Laggard_pre* from 2008 to 2010	4,079	4.484	10.184	0	1	4

Panel B: Summary Statistics of Firm Characteristics

VARIABLES	N	Mean	SD	P25	Median	P75	Compustat	
							N	Median
Size	4,079	6.766	2.281	5.002	6.775	8.388	29,213	5.904
CAPX	4,079	0.031	0.031	0.012	0.023	0.040	29,213	0.033
BM	4,079	0.729	0.522	0.381	0.625	0.950	29,213	0.865
ROA	4,079	-0.126	0.510	-0.147	0.028	0.077	29,213	0.091
Leverage	4,079	0.191	0.242	0.001	0.149	0.286	29,213	0.193
Loss	4,079	0.403	0.491	0.000	0.000	1.000	29,213	0.000
R&DExp	4,079	0.146	0.206	0.024	0.071	0.172	29,213	0.000

Notes: This table provides descriptive statistics of our sample and key variables. Panel A reports summary statistics on laggard, patent filings and publications. Panel B reports the distribution of firm characteristics in our sample, as compared with the Compustat universe over the same sample period (2008 to 2010; 2013 to 2015).

Table 2: Pearson Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Laggard_pre	1.00									
(2) Post	-0.00	1.00								
(3) Pub	0.16*	-0.00*	1.00							
(4) Patent	0.29*	0.00	0.24*	1.00						
(5) Exit	-0.29*	-0.00	-0.24*	-1.00*	1.00					
(6) Size	0.11*	0.03*	0.39*	0.15*	-0.15*	1.00				
(7) BM	0.00*	-0.22*	0.02*	0.00*	-0.00*	0.09*	1.00			
(8) Leverage	0.01*	0.06*	0.03*	0.02*	-0.02*	0.19*	-0.05*	1.00		
(9) ROA	0.03*	-0.00*	0.11*	0.04*	-0.04*	0.48*	0.07*	-0.17*	1.00	
(10) R&DExp	-0.04*	-0.01*	-0.12*	-0.05*	0.05*	-0.57*	-0.22*	0.02*	-0.67*	1.00
(11) CAPX	0.02*	-0.03*	0.07*	0.02*	-0.02*	0.19*	0.02*	0.07*	0.08*	-0.12*
(12) Loss	-0.05*	0.01*	-0.16*	-0.07*	0.07*	-0.55*	0.08*	0.00*	-0.50*	0.50*

Notes: Table 2 reports the Pearson covariance matrix among the variables of our main tests and firm characteristics. * indicates correlations statistically significant at the 10% level.

Table 3: AIA and Innovation Activities

Panel A: AIA and Number of Patent Filings

VARIABLES	(1) Patent	(2) Patent	(3) Patent	(4) Patent	(5) Patent	(6) Patent
Laggard_pre×Post	**-0.097***** **(0.000)**	**-0.097***** **(0.000)**	**-0.099***** **(0.000)**	**-0.104***** **(0.000)**	**-0.112***** **(0.000)**	**-0.115***** **(0.000)**
Laggard_pre	0.321*** (0.000)	0.253*** (0.000)	0.254*** (0.000)			
Post	0.001*** (0.002)					
Constant	0.009*** (0.000)					
Observations	1,884,498	1,884,498	1,884,498	1,884,498	1,884,498	1,884,498
Adjusted R-squared	0.087	0.167	0.167	0.556	0.559	0.559
Firm FE	No	Yes	Yes	No	No	No
Year FE	No	Yes	No	No	No	No
TechClass FE	No	Yes	No	No	No	No
Firm×Year FE	No	No	No	No	Yes	Yes
Firm×TechClass FE	No	No	No	Yes	Yes	Yes
TechClass×Year	No	No	Yes	Yes	No	Yes

Panel B: AIA and Exit of Technological Competition

VARIABLES	(1) Exit	(2) Exit	(3) Exit	(4) Exit	(5) Exit	(6) Exit
Laggard_pre×Post	**0.140***** **(0.000)**	**0.139***** **(0.000)**	**0.142***** **(0.000)**	**0.151***** **(0.000)**	**0.161***** **(0.000)**	**0.165***** **(0.000)**
Laggard_pre	-0.463*** (0.000)	-0.365*** (0.000)	-0.366*** (0.000)			
Post	-0.002*** (0.002)					
Constant	0.987*** (0.000)					
Observations	1,884,498	1,884,498	1,884,498	1,884,498	1,884,498	1,884,498
Adjusted R-squared	0.087	0.167	0.167	0.556	0.559	0.559
Firm FE	No	Yes	Yes	No	No	No
Year FE	No	Yes	No	No	No	No
TechClass FE	No	Yes	No	No	No	No
Firm×Year FE	No	No	No	No	Yes	Yes
Firm×TechClass FE	No	No	No	Yes	Yes	Yes
TechClass×Year	No	No	Yes	Yes	No	Yes

Notes: Table 3 presents the results of estimating Eq. 1: the impact of the AIA on corporate innovation activities. In Panel A, we examine the number of patent filings, and in Panel B the focus is on the exit of technological competition. All continuous variables are winsorized at the top and bottom 1%. The standard errors are clustered at firm level. P-values are reported in parentheses. *,**,*** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

Table 4: AIA and Corporate Scientific Publications (H1)

VARIABLES	(1) Pub	(2) Pub	(3) Pub	(4) Pub	(5) Pub	(6) Pub
Laggard_pre×Post	**0.051****	**0.058*****	**0.062*****	**0.049*****	**0.026****	**0.025*****
	(0.018)	**(0.003)**	**(0.001)**	**(0.008)**	**(0.014)**	**(0.008)**
Laggard_pre	1.347***	0.392***	0.389***			
	(0.000)	(0.000)	(0.000)			
Post	-0.008					
	(0.396)					
Constant	0.379***					
	(0.000)					
Observations	1,884,498	1,884,498	1,884,498	1,884,498	1,884,498	1,884,498
Adjusted R-squared	0.026	0.577	0.577	0.867	0.898	0.898
Firm FE	No	Yes	Yes	No	No	No
Year FE	No	Yes	No	No	No	No
TechClass FE	No	Yes	No	No	No	No
Firm×Year FE	No	No	No	No	Yes	Yes
Firm×TechClass FE	No	No	No	Yes	Yes	Yes
TechClass×Year	No	No	Yes	Yes	No	Yes

Notes: Table 4 presents the results of estimating Eq. 2: the impact of the AIA on corporate scientific publications. All continuous variables are winsorized at the top and bottom 1%. The standard errors are clustered at firm level. P-values are reported in parentheses. *,**,*** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

Table 5: Sub-sample Analyses – Inventor Mobility

VARIABLES	(1) LowIDD	(2) HighIDD	(3) LowMoveInvtr	(4) HighMoveInvtr
Laggard_pre×Post	**0.025**** **(0.016)**	**0.028** **(0.191)**	**0.014** **(0.309)**	**0.028***** **(0.008)**
Observations	951,258	933,240	942,249	942,249
Adjusted R-squared	0.920	0.830	0.878	0.915
Firm×Year FE	Yes	Yes	Yes	Yes
Firm×TechClass FE	Yes	Yes	Yes	Yes
TechClass×Year	Yes	Yes	Yes	Yes

Notes: Table 5 reports the regression results from regression scientific publications on the treatment variable interacted with post for by subsamples of firms affected by the IDD (columns 1 and 2) and inventory mobility (columns 3 and 4). All continuous variables are winsorized at the top and bottom 1%. The standard errors are clustered at firm level. P-values are reported in parentheses. *,**,*** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

Table 6: Sub-sample Analyses – Firm Characteristics

Panel A: Importance of Foreign Patent

	(1)	(2)	(3)	(4)
	Foreign Family		Foreign Priority	
VARIABLES	Local	Foreign	Local	Foreign
Laggard_pre×Post	**0.090****	**0.022****	**0.080*****	**0.013**
	(0.010)	**(0.023)**	**(0.002)**	**(0.195)**
Observations	946,176	938,322	1,075,536	808,962
Adjusted R-squared	0.798	0.912	0.799	0.918
Firm×Year FE	Yes	Yes	Yes	Yes
Firm×TechClass FE	Yes	Yes	Yes	Yes
TechClass×Year	Yes	Yes	Yes	Yes

Panel B: Financial Constraints

	(1)	(2)	(3)	(4)
	Leverage		Debt-to-Cash	
VARIABLES	Low	High	Low	High
Laggard_pre ×Post	0.020	0.028**	0.013	0.035***
	(0.218)	(0.032)	(0.381)	(0.009)
Observations	914,298	970,200	914,298	970,200
Adjusted R-squared	0.888	0.904	0.897	0.899
Firm×Year FE	Yes	Yes	Yes	Yes
Firm×TechClass FE	Yes	Yes	Yes	Yes
TechClass×Year	Yes	Yes	Yes	Yes

Notes: Table 6 presents results for cross-sectional analyses based on two firm characteristics. Panel A presents results of estimating Eq. 2 for subsamples of firms based on the number of foreign patents filed during pre-AIA period (1991 to 2010). Columns (1) and (2) categorize foreign patents based on whether a patent seeks protection in foreign jurisdictions ("foreign family"), while Columns (3) and (4) classify foreign patents according to whether each patent's initial filing was in a foreign jurisdiction ("foreign priority"). Local (Foreign) is defined as firms having the number of foreign patents below (above) the sample median. Panel B presents results of estimating Eq. 2 for sub-samples of firms based on financial constraints during pre-AIA period (2008 to 2010). Columns (1) and (3) include firms with below-industry-median financial constraints and Columns (2) and (4) include firms with above-industry-median financial constraints. All continuous variables are winsorized at the top and bottom 1%. The standard errors are clustered at firm level. P-values are reported in parentheses. *,**,*** indicate statistical significance at the 10, 5, and 1 percent level, respectively. All variables are defined in Appendix A.

Table 7: Sub-sample Analyses – Technology Class Characteristics

Panel A: Access to Legal Expertise

	(1)	(2)
	Attorney	
VARIABLES	Low	High
Laggard_pre×Post	**0.028*** **	**0.011**
	(0.003)	**(0.556)**
Observations	942,249	942,249
Adjusted R-squared	0.909	0.884
Firm×Year FE	Yes	Yes
Firm×TechClass FE	Yes	Yes
TechClass×Year	Yes	Yes

Panel B: Barriers to Entry

	(1)	(2)	(3)	(4)
	Concentration		#Competitors	
VARIABLES	Low	High	Low	High
Laggard_pre ×Post	**0.016**	**0.039*** **	**0.007**	**0.028*** **
	(0.134)	**(0.002)**	**(0.766)**	**(0.002)**
Observations	942,249	942,249	942,249	942,249
Adjusted R-squared	0.902	0.894	0.885	0.909
Firm×Year FE	Yes	Yes	Yes	Yes
Firm×TechClass FE	Yes	Yes	Yes	Yes
TechClass×Year	Yes	Yes	Yes	Yes

Notes: Table 7 presents results for cross-sectional analyses based on two technology class characteristics. Panel A presents results of estimating Eq. 2 for sub-samples of technological classes based on unique number of attorneys filing patents in each class, scaled by the total number of patents filed pre-AIA period (1991 to 2010).
Panel B presents results of estimating Eq. 2 for sub-samples of technological classes based on the intensity of technological competition in each class during pre-AIA period (1991 to 2010). Columns (1) and (2) measure technological competition based on the percentage of patents filed by the top 3 most activate firms in each tech class. Columns (3) and (4) measure technological competition based on the number of firms filing patents in each class. All continuous variables are winsorized at the top and bottom 1%. The standard errors are clustered at firm level. P-values are reported in parentheses. *,**,*** indicate statistical significance at the 10, 5, and 1 percent level, respectively. All variables are defined in Appendix A.

Table 8: Robustness Tests

Panel A: Alternative Definition of Laggard

	(1)	(2)	(3)
VARIABLES	Count	%KPSS-wt	%Citation-wt
Laggard_pre×Post	**0.022****	**0.027*****	**0.022****
	(0.038)	**(0.004)**	**(0.036)**
Observations	1,884,498	1,884,498	1,884,498
Adjusted R-squared	0.898	0.898	0.898
Firm×Year FE	Yes	Yes	Yes
Firm×TechClass FE	Yes	Yes	Yes
TechClass×Year	Yes	Yes	Yes

Panel B: Alternative Link between Patent Classes and Publication Fields

	(1)	(2)	(3)
VARIABLES	Rank 1	Rank 5	Above 5%
Laggard_pre×Post	**0.025*****	**0.025*****	**0.029*****
	(0.008)	**(0.008)**	**(0.002)**
Observations	1,884,498	1,884,498	1,884,498
Adjusted R-squared	0.898	0.898	0.912
Firm×Year FE	Yes	Yes	Yes
Firm×TechClass FE	Yes	Yes	Yes
TechClass×Year	Yes	Yes	Yes

Table 8: Robustness Tests Continued

Panel C: Falsification Test

	Actual Data	Shuffled Laggard_pre	Prob. B1_shuffled> β1_actual data [p-value]
Laggard_pre×Post	**0.025*** **	**0.000086**	[<0.001]
	(2.649)	**(0.475)**	

Notes: Table 8 reports the results of robustness tests. Panel A presents the regression results of our main tests on corporate scientific publications using 3 alternative ways to define laggard. Laggard is measured as 1) an indicator variable equal to 1 if the number of patent stocks in a given technology class is below the bottom quartile of its tech peers in Column 1; 2) an indicator variable equal to 1 if the percentage of commercial-value-weighed patent stocks in a given technology class is below the bottom quartile of its tech peers in Column 2; 3) an indicator variable equal to 1 if the percentage of citation-weighted patent stocks in a given technology class is below the bottom quartile of its tech peers in Column 3. Panel B presents the regression results of our main tests on corporate scientific publications using 3 alternative ways to construct the link between patent tech classes and publication science fields. A publication science field is linked to a patent tech class if 1) it is the top 1 publication field that the patents in the tech class cite most in Column 1; 2) it is the top 5 publication field that the patents in the tech class cite most in Column 2; 2) citations to papers in the science field account for more than 5% of all the citations from the patents in the tech class in Column 3. Panel C presents the results of estimating Eq. 2 based on 1,000 random samples where Laggard_pre classes are randomly shuffled within each firm. All continuous variables are winsorized at the top and bottom 1%. The standard errors are clustered at firm level. P-values are reported in parentheses. *,**,*** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

Table 9: Peer Firms' Patent Rejections

VARIABLES	(1) %NoveltyRej	(2) %ObviousRej
Laggard_pre×Post	**0.012***** **(0.000)**	**0.050***** **(0.000)**
Patent Application	0.092*** (0.000)	0.104*** (0.000)
Observations	1,884,498	1,884,498
Adjusted R-squared	0.315	0.406
Firm×Year FE	Yes	Yes
Firm×TechClass FE	Yes	Yes

Notes: Table 9 reports the regression results of estimating Eq. 4: the impact of the AIA on peer firms' patent applications that received novelty or obviousness rejections. The dependent variables are peer firms' patent applications in the same tech classes that are rejected for novelty and obviousness reasons as a percentage of all peer firms' patent applications rejected for any reason. The standard errors are clustered at firm level. P-values are reported in parentheses. *,**,*** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

Appendix A: Variable Definitions

Variable Name	Definition
Attorney	The number of unique attorneys that have filed patents in class j scaled by the number of patents in that class between 1991 and 2010.
BM	Book-to-market ratio at the end of year t (Compustat items AT / (PRCC_F*CSHO + DLTT + DLC)) for firm i.
CAPX	Capital expenditures scaled by total assets at the end of year t (Compustat items CAPX / AT) for firm i.
Class	The number of classes in which firm i files patents during year t.
#Competitors	The number of unique firms that have filed patents in class j between 1991 and 2010.
Concentration	The percentage of patents filed by the top three most active firms in class j, relative to the total number of patents filed in that class, between 1991 and 2010.
Debt-to-Cash Ratio	Total liabilities scaled by total cash at the end of year t (Compustat items (DLTT + DLC) / CHE) for firm i.
Exit	An indicator variable that equals 1 if firm i does not file any patents in class j during year t.
Foreign Family	The median split of the number of patents that seek protection in foreign jurisdictions from firm i between 1991 and 2010.
Foreign Priority	The median split of the number of patents that first filed in a foreign jurisdiction from firm i between 1991 and 2010.
Laggard	An indicator variable that equals 1 if firm i is lagging in a patent class j for which they have on-going R&D activity during year t. A firm-class is defined as a laggard class for firm i in year t if its number of patents in this class from year t-20 to year t-1 with 15% annual depreciation rate, as a percentage of the firm's total patents over the same window, is below the 25th percentile among all firms that file patents in this class in year t.
Laggard_pre	An indicator variable that equals 1 if firm i is a laggard in patent class j (i.e., *Laggard Class* = 1) in any of the 3 pre-AIA years: 2008, 2009, or 2010.
Laggard-Count	An indicator variable that equals 1 if firm i is lagging in a patent class j for which they have on-going R&D activity during year t. A firm-class is defined as a laggard class for firm i in year t if its number of patents in this class from year t-20 to year t-1 with 15% annual depreciation rate is below the 25th percentile among all firms that file patents in this class in year t.
Laggard-%KPSS-wt	An indicator variable that equals 1 if firm i is lagging in a patent class j for which they have on-going R&D activity during year t. A firm-class is defined as a laggard class for firm i in year t if the total value of patents in this class from year t-20 to year t-1 with 15% annual depreciation rate, as a percentage of the total value of firms' patents over the same window, is below the 25th percentile among all firms that

	file patents in this class in year t. Patent value is constructed by Kogan et al. (2017).
Laggard-%Citation-wt	An indicator variable that equals 1 if firm i is lagging in a patent class j for which they have on-going R&D activity during year t. A firm-class is defined as a laggard class for firm i in year t if the citation-weighted patents in this class from year t-20 to year t-1 with 15% annual depreciation rate, as a percentage of firms' total citation-weighted patents over the same window, is below the 25th percentile among all firms that file patents in this class in year t. The citation weight is the number of future patents that cite a focal patent.
Leverage	Total liabilities scaled by total assets at the end of year t (Compustat items (DLTT + DLC) / AT) for firm i.
Loss	An indicator variable that equals 1 if net income (Compustat item NI) is less than 0 for year t for firm i.
%NoveltyRej_Peer	The number of firm i's tech peers' patent applications filed in class j in year t later rejected due to lack of novelty, divided by the number of tech peers' patent applications filed in class j in year t later rejected for any reason.
%ObviousRej_Peer	The number of firm i's tech peers' patent applications filed in class j in year t later rejected due to lack of obviousness, divided by the number of tech peers' patent applications filed in class j in year t later rejected for any reason.
Patent Application_peer	The number of firm i's tech peers' patent applications filed in class j in year t.
Patent	The natural logarithm of 1 plus the number of patents filed by firm i in class j during year t.
Post	An indicator variable that equals 1for post-AIA years: 2013, 2014, and 2015.
Pub	The natural logarithm of 1 plus the number of academic publications by firm i in class j during year t.
R&DExp	R&D expenses scaled by total assets at the end of year t (Compustat items XRD / AT) for firm i.
ROA	Net income scaled by total assets at the end of year t (Compustat items NI / AT) for firm i.
Size	The natural logarithm of total assets at the end of year t (Compustat item AT) for firm i.
Tangibility	Net value of property, plant, and equipment scaled by total assets at the end of year t (Compustat items PPENT /AT) for firm i.

Online Appendix
for
"Strategic Scientific Disclosure: Evidence from the Leahy-Smith America Invents Act"

OA1. Sample Selection Procedures

We construct our sample in four steps. First, we begin with all Compustat firm-years from 2008 to 2010 and 2013 to 2015 with non-missing scientific publication information from Arora et al. [2021].[27] We leave out the years 2011 and 2012, between the AIA announcement date and the effective date, in order to remove anticipatory effects. The Arora et al. [2021] sample includes Compustat industrial firms that are headquartered in the U.S., have at least one patent, and have positive R&D expenses for at least one year from 1980 to 2015. We further require firms to have at least one scientific publication over the sample period. Arora et al. [2021] match Compustat firms to their academic articles covered in the "Science Citation Index" and "Conference Proceedings Citation Index-Science" with Compustat firms based on authors' affiliation.[28] We further exclude companies from the financial industry (SIC 6000-6999). This step leaves us with 1,785 unique firms with significant representation from the manufacturing, service, transportation, and communications industries.

Second, Arora et al. [2021] provide only the publication count for each firm year, but our main analyses require us to identify the technology area to which individual scientific publications pertain. To obtain more granular publication-level data for our main analysis, we create a crosswalk between our sample firms and author affiliations of each publication from the OpenAlex database, an open-source database for scientific publications.[29]

[27] We thank Arora et al. [2021] for kindly sharing their data on corporate scientific publications: https://zenodo.org/record/4320782#.YhKskOjMKUk.

[28] "Science Citation Index" and "Conference Proceedings Citation Index-Science" provide comprehensive coverage on science academic articles, excluding social sciences, arts, and humanities articles. "Science Citation Index" indexes over 9,500 journals with more than 53 million records. "Conference Proceedings Citation Index-Science" indexes over 227,000 conference proceedings. Coverage from these two indexes includes both basic science and applied science (Arora et al. [2018]).

[29] We obtain corporate scientific publications at the technology class level from the OpenAlex database instead of the Web of Science database as in Arora et al. [2021] due to data availability. OpenAlex is an open-source database for scientific publications that offers comparable coverage as other commercial sources such as the Web of Science. See https://openalex.org for details.

To construct the link between public firms and individual scientific publications (rather than the total count of publications available from Arora et al. 2021), we rely on author affiliations from OpenAlex. We begin with sample firms that published at least one paper during 2008 to 2015 from Arora et al. [2021]. We then obtain both parent firm names and subsidiary names from Arora et al. [2021] and fuzzy match them with author affiliation names from OpenAlex. We then manually check potential matched pairs with cosine similarity score above 0.6 to identify valid matches. For any remaining unmatched sample firms, we manually identify unique keywords of each company name and then manually checked all author affiliations that contain those keywords. These procedures yield successful matches for 821 firms with scientific publication matches from OpenAlex.

Third, we obtain corporate patent data from Kogan et al. [2017] and subsequently merge it with detailed patent characteristics from PatentsView, which contains the patent technology class. Specifically, we use the Cooperative Patent Classification (CPC) system at the subclass level of aggregation (e.g., A63B), which has 657 distinct patent technology classes.

Fourth, we construct a link between a patent technology class and scientific publication field. For each scientific publication, we obtain the scientific field information from the Web of Science, which classifies scientific publications into 251 fields. We link patent technology classes to scientific publication fields based on patent citations to scientific publications from the Reliance on Science database. Specifically, we define a scientific publication field as linked to a patent class if it ranks among the top three most-cited scientific publication fields by all the patents in that class. In section 6.1, we explore the robustness of our results to alternative methods in linking a patent class to publication fields.

We establish the link between patent technology classes and scientific publication fields using publications from the pre-AIA period (1991 to 2010). Out of the 657 patent classes, 195 were excluded because no patents within those classes cited any scientific publications from 1991 to 2010 based on the Reliance on Science database, leaving 462 patent classes. This could be due to either no patents being filed during that period, or patents being filed but without citing any scientific publications. Additionally, only 120 of the 251 possible scientific publication fields were cited by patents and ultimately, we link 462 patent classes to 120 scientific publication fields. Our sample spans six years and each of the 821 sample firms can compete in any of these 462 patent classes. If every firm appeared in each of the six sample years, there would be 821 firms x 462 patent classes x 6 years =2,275,812 observations. Our final sample size is slightly smaller because not every firm is in the sample in Compustat for all six years, yielding a final sample of 1,868,790 firm-year-patent class observations for our main analyses.

Our final sample includes firm-year-patent class observations for which there are zero patents and scientific publications. We include these observations to allow for the possibility that firms change their innovative activity and later move into those tech classes. Excluding those classes where firms currently do not have any innovative activity could introduce potential bias to our estimation by focusing on only those self-selected technology areas. To account for firms' self-selection into specific innovation space, we include the firm-by-tech class fixed effects, which control for the general activity level each firm has in a technology space. This empirical choice follows the common gravity model in international trade literature (e.g., Head et al. [2011]). In addition, an important feature of our design as discussed in section 4.3.1 is the use of high dimensional fixed effects, including firm-by-year, year-by-tech class, and firm-by-tech class fixed effects. The balanced panel in our sample facilitates the inclusion of these high dimensional fixed effects.

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