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

Abstract

We examine the impact of technological competition on voluntary innovation disclosure using changes scientific publications around the enactment of Leahy-Smith America Invents Act of 2011 (AIA). The AIA changes the patent system from first-to-invent to first-inventor-to-file system and induces a patent "race" that increases technological competition. Firms with resource constraints tend to be slow in filing a patent and are disadvantaged in this race. Using a difference-in-differences design, we show that financially constrained firms strategically increase scientific publications in an attempt to block competitors from obtaining a patent and extend the patent race after the enactment of AIA. This effect is more pronounced among firms (1) that are less capital intensive, and whose competitors have a lower cost of entry; (2) that face more patent competition; and (3) whose patents have longer lifecycles. The findings suggest that technological competition is a key determinant of firms' scientific publications. The positive effect of the AIA on corporate scientific publications is consistent with the policy makers' goal to promote knowledge spillover in society.

1. Introduction

In this study, we examine the conditions under which technological competition can increase voluntary innovation disclosure. While traditional wisdom argues that disclosing innovations in a competitive environment opens firms to significant proprietary costs and thus should deter voluntary innovation disclosure (Cao et al. 2018), we argue that for firms who lag behind competition, disclosure can be used as a measure of last resort to sabotage rivals. Specifically, we investigate whether financially constrained firms are more likely to disclose R&D outputs in scientific publications as a strategy to negate rivals' patentability after an increase in technological competition. Scientific publications become public knowledge, thereby raising the bar for inventors to claim their related technologies are novel, reducing the likelihood of obtaining a patent. A financially constrained firm that believes a rival is likely to complete an invention first might therefore try to publish their scientific findings to defeat the rival's patent prospects. We posit that financially constrained firms increasingly employ strategic scientific publications after a recent U.S. patent law change, which led to a race to the patent office and made pre-emptive publications a more viable strategy.

The Leahy-Smith America Invents Act of 2011, the most substantial patent legislation reform since 1952, switches the patent grant base from the "first-to-invent" to the "first-inventor-to-file" system. Under the "first-to-invent" system, the entity that has the right to file a patent application is the "first" or original inventor. The recognition of the "first" inventor is based on all public and private evidence, such as laboratory notes. In contrast, for patents filed under the AIA, priority is given to the inventor who first files the application, regardless of whether she is the original inventor. Therefore, firms' R&D secrecy becomes unserviceable in the ever-accelerated patent race under the post-AIA "first-inventor-to-file" regime.

Firms with adequate resources may benefit from the “first-inventor-to-file” system because they can quickly evaluate an invention and file a patent application. In contrast, for firms with insufficient resources to expedite patent applications, scientific publications can be a strategic reaction to the post-AIA patent race. First, scientific publications, in general, become “prior art” (public knowledge) and are not patentable; however, in the U.S., the focal publishing firm will receive a one-year grace period, during which the firm has the exclusive right to patent the disclosed invention. Scientific publications are a viable method that substitutes the private records for claiming a patent and winning the firm extra time to submit the patent application post-AIA.

Second, publishing an invention raises the bar for competitors to patent their inventions, thus extending the patent race. By doing so, financially constrained firms could have more time to catch up in the patent race (Baker and Mezzetti, 2005). Finally, publishing an invention can be a defensive strategy when a firm expects itself to lose the patent race: by making the invention public knowledge, the firm could prevent the competitor from patenting the invention and getting monopoly power, thereby retaining the flexibility to commercialize the invention (Parchomovsky, 2000). For the above reasons, we conjecture that firms with financial constraints are more likely to use pre-emptive scientific publication during the patent race post-AIA.

We employ a difference-in-differences (DID) design and examine whether firms with greater financial constraints increase their scientific publications more in the post-AIA period relative to less constrained firms. Our empirical analyses are based on a sample of Compustat firms from 2009 to 2015 with corporate scientific publication information from Arora et al. (2021). Arora et al. (2021) match academic articles covered by “Science Citation Index” and “Conference Proceedings Citation Index-Science” to U.S. public firms based on authors’ affiliations. We measure a firm's financial constraints as the average industry-adjusted book leverage over the sample period. We find that scientific publications of firms with higher financial leverage increase significantly after the enactment of the AIA and do so more than less constrained firms. Specifically, relative to low-leverage firms (25^{th} percentile), high-leverage firms (75^{th} percentile) increase the number of scientific publications by 2.5% post-AIA.

We also perform two robustness analyses to ensure reliability of our main results. First, to address the concern that financial leverage captures other firm characteristics that are not related to AIA but affect a firm's publication decisions, we examine the effect of AIA on scientific publications based on propensity-score matched sample with entropy balancing. Our results are consistent with the main findings, which mitigates endogeneity concerns. Next, we perform a placebo test, where we assume AIA was enacted two years prior to the actual date. We do not find a significant change in scientific publications around the pseudo-event date, which suggests our main findings are unlikely driven by some other unmeasured factors that changed over time. Overall, the findings are consistent with our hypothesis that firms increase scientific publications in response to technological competition.

Cross-sectionally, we find that the effect of AIA on the frequency of scientific publication among highly leveraged firms is more pronounced when (1) there are lower entrance costs for competitors as proxied for by focal firm size and capital intensity, (2) the firm faces greater competition, and (3) the firm's inventions have longer lifecycles and therefore patent protections are more important.

In additional analysis, we also explore the channels why resource-constrained firms increase scientific publications. We find that rivals of firms with more scientific publications have fewer future patent filings after the implementation of the AIA, consistent with a firm's scientific publications reducing the likelihood that competitors receive a patent for an invention. Interestingly, we also find that the disclosing firm's own patent filings decrease in the post-AIA period as a function of scientific disclosure, suggesting that the scientific disclosures also prevent the disclosing firm from obtaining patent protection for an invention. Taken together, our evidence is consistent with pre-emptive publication to deter competition instead of securing a patent using the 12-month grace period.

We contribute to the literature about the effects of competition on voluntary innovation disclosure. We find that technological competition leads to an increase in voluntary innovation disclosure for financially constrained firms. While Cao et al. (2018) document a negative relation between competition and voluntary innovation disclosure on average, we highlight the importance that financial constraints have to affect firms' disclosure strategies in the presence of technological competition. Glaeser and Landsman (2021) find an increase in *product market competition* can induce firms to voluntarily accelerate the disclosure of inventions pending patent protection (an increase in voluntary innovation disclosure), while *technological competition* is associated with greater patent disclosure delays (a decrease in voluntary innovation disclosure). Our findings complement Glaeser and Landsman (2021) by demonstrating that deterrent disclosure can also occur even when firms' disclosures come at the expense of receiving patent protection for their inventions, a costly real effect of disclosure.

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. Nevertheless, 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 from which the focal firm benefits in follow-up innovations. We show that the patent race following AIA results in resource-constrained firms strategically increasing voluntary innovation disclosure through publications.

Finally, this is one of the first papers that examine the consequence of the AIA on firms' innovation disclosures. The AIA is the most significant patent legislation reform since 1952. The consequences of the AIA are of substantial interest to various parties, including regulators, technocrats, and academics (Abrams and Wagner, 2013). Huang et al. (2021) show an average decline in innovating firms' general R&D disclosures, measured as the number of sentences containing R&D keywords in 10-k, after the AIA. They conclude that the AIA negatively impacts firms' voluntary R&D disclosure due to increased proprietary costs. An important fact that was less relevant to general R&D disclosure in the 10-k setting is the function of public disclosure as "prior arts". Unlike general R&D disclosure, technical and detailed R&D disclosure such as scientific publications function as "prior art" and grant the publishing firm the exclusive right to patent the invention. This paper complements Huang et al. (2021) by documenting a positive effect of the AIA on firms' scientific disclosures.

The rest of the paper is organized as follows. Section 2 introduces institutional background on the Leahy-Smith America Invents Act and corporate scientific publications. Section 3 develops the hypotheses. Section 4 describes the empirical design. Section 5 presents the results. Section 6 provides additional analyses, and Section 7 concludes.

2. Institutional Background

2.1 The Leahy Smith America Invents Act

The Leahy-Smith America Invents Act of 2011 (AIA) is the most significant legislative change to the U.S. patent system since 1952. Among others, the law switched the U.S. patent grant rule from a "first-to-invent" to a "first-inventor-to-file" system. Specifically, before the AIA, the patent applicant who is proved to be the first inventor will be granted the patent ("first-to-invent"). The recognition of "first inventor" is at the discretion of the U.S. Patent and Trademark Office (USPTO) after taking all relevant evidence into consideration, including an inventor's private records. After the AIA, among multiple inventors who try to claim the same invention, the one who first files the patent application will win the patent race, even though he/she is not the first inventor ("first-inventor-to-file").

Figure 1 plots the timeline of the AIA enactment. The switch to the "first-inventor-to-file" system is applied to patent applications filed on or after March 16, 2013. To demonstrate the change, let us consider two biologists that investigate the same gene-editing technology. Biologist A made some breakthroughs on January 1, 2022, and recorded such findings in her laboratory notebook on the same date. On May 1, 2022, biologist B discovered the same technology and immediately filed a patent application on May 10, 2022. One month after biologist B's patent application, biologist A also filed her patent application. In this dynamic, 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.

The discussions on AIA, since its launch, have centered around fairness and efficiency (Merges, 2012; Gatzemeyer, 2015). The "first-to-invent" patent system before the AIA awards the one who first comes up with an invention the credits, thus being a relatively fair practice. However, in practice, identifying the first inventor would require the Supreme Court 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 from "first-to-invent" to "first-inventor-to-file" through the AIA improves the cost efficiency while sacrificing fairness. The legal protection of R&D secrecy is weakened post-AIA, and firms are forced to run a race to file their patents. Such a race benefits firms with adequate resources and flexibility to accelerate their patent applications, while putting others at a disadvantage (Abrams and Wagner, 2013).

Voluntary disclosures before patent application play an essential role in this patent race post-AIA. Under both "first-to-invent" and "first-inventor-to-file," public disclosures, as well as public use or sale, of an invention before patent application grant the publisher exclusive rights to file the patent application. Under 35 U.S.C. §102(a) and (b), public disclosures of an invention will be viewed as public knowledge and not patentable, except for the publishing firm. The firm that publishes the knowledge has a 1-year "grace period" to file the patent application. Based on a sample of paired patents with scientific publications, Franzoni and Scellato (2010) show that the grace period treatment is used by nearly one-third of the U.S. patents filed by academic inventors. Scientific publications are an ideal disclosure channel, as academic articles contain sufficient details that can be directly linked to the invention to be patented. Actually, scientific publications, along with existing patents, are the major "prior art" that patent examiners search for when they process patent applications. Assuming in the gene-editing technology example, biologist A publishes her finding in an academic paper on March 1, 2022. This publication will lead to the rejection of biologist B's patent application but will allow biologist A to receive the patent, since biologist A files the application within one year after March 1, 2022. **Figure 2** summarizes the consequence of the transmission from "first-to-invent" to "first-inventor-to-file" after the AIA.

2.2 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, up to 2021, IBM hired over 100 in-house scientists whose academic work received more than 10,000 citations based on Google Scholar.[1] 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 that specializes in scientific, technical, and medical content, during 2020, about 126,000 out of 560,000 academic articles 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 open-source academic journals remains arguably puzzling. Corporate scientific publications trigger knowledge spillover

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

and create significant proprietary costs to the publishing firm, more so than patents (Arora et al., 2021; Gans et al., 2017). Such proprietary costs should discourage firms from publishing their research outputs in academic journals.

A series of research unravels this puzzle by documenting several strategic benefits. First, firms publish academic articles for their suppliers and customers. Harhoff et al. (2004) demonstrate that disclosing in-house research output to suppliers could get suppliers on board, who would 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 gives them self-fulfillment and is a common human resource instrument to attract and retain talent (Stern, 2004; Sauermann and Roach, 2014). Shen (2021) then documents the reciprocity of AI-related corporate scientific publications: a firm's scientific publications benefit external follow-up patents, building on which the focal firm's patents also become more valuable and less risky. Finally, investors also demand such information on firms' early-stage research output (Baruffaldi et al., 2020).

Prior studies discuss two IP strategies to take advantage of scientific publications and the one-year grace period under the U.S. patent law. First, disclosures by one firm raise the novelty requirement for competitors to claim a related patent, therefore extending the patent race. In this extended patent race, the disclosing firm, which may be behind at the current stage, could have more time and thus a better opportunity to catch up (Baker and Mezzetti, 2005). Second, when a firm realizes that it is unlikely to win the race, or that patenting the invention is not worth the costs, the firm might decide to drop out of the patent race in this round. However, 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 firm could not patent it and gain monopoly power (Parchomovsky, 2000; Johnson, 2014).

The shift from "first-to-invent" to "first-inventor-to-file" system has arguably made pre-emptive publication a more attractive strategy for a lagging firm to prevent a leading firm to file a patent in the post-AIA patent race. Under the "first-to-invent" system, it is difficult if not impossible, for a lagging firm to defeat the patent claims of a leading firm by publishing interim research results. The leading firm could avoid the publication as prior art by proving *private record* that it had already progressed as far as the lagging firm as of the publication date. Under this system, pre-emptive publication can only work if deployed at least a year prior to the application filing date of the leading firm (Eisenberg 2000). The "first-to-file" system under AIA, in contrast, makes the pre-emptive publication an effective strategy for a lagging firm, because private records are no longer a consideration.

In summary, the fact that private records are no longer considered as evidence for IP protection under the AIA has two implications. First, if a firm has difficulty gathering resources to accelerate patent application quickly, they could leverage academic publications to secure their right to file patent applications. Second, it becomes a more appealing strategy to block a competitor in a patent race through scientific publication.

3. Hypothesis development

3.1 Technological competition, financial constraints, and scientific disclosure

Recent research emphasizes the heterogenous 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 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, and thus their measure has features of both product and technological competition.

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, which does not preclude the disclosing firm from obtaining protection patent grant. In contrast, scientific publications do not impart intellectual property protection and in fact are frequently included as citations in patent applications (Jaffe and de Rassenfosse 2019), thus increasing the potential competitive costs for disclosing firms.

Competitive costs — imparting proprietary information to existing and potential competitors — is 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 would take a significant amount of time. Legal protection on firms' internally developed

IP determines firms' competitive costs and thus their disclosure practice. A weakened legal protection system on firms' private R&D activities makes keeping an invention secret less beneficial and reduces the opportunity cost of public disclosures.

The first-to-file system under AIA, as opposed to first-to-invent system, essentially shift emphasis on the speed of filing instead of the speed of invention. This shift is likely to disadvantage firms with limited resources, which are generally slower in filing patent applications (Joachim 2015). In contrast, firms with adequate resources could integrate resources, such as scientific and legal support, more efficiently and quickly to assess an invention and file a patent application, benefiting from the "first-inventor-to-file" system.

We conjecture that resource constrained firms are more likely to react to AIA by increased scientific publication post AIA for two reasons. First, the 12-month grace period can delay the start of the patent application, which is desirable when the firm needs more time to gather resources to bring the invention to market.[2] Second, resource constrained firms are more likely to engage in strategic disclosure. 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). Since 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. In this case, disclosure raises the bar for others to file for a patent and in essence extends the race, so that the focal firm can catch up with the race even if it is currently falling behind. In the worst scenario, if the disclosing firm does not itself plan to pursue patents related to the disclosed information, disclosure serves as a defensive mechanism

[2] However, conversations with practitioners suggest that firms generally file a patent before publishing a paper due to proprietary costs concern. Another factor that prevents a multi-national firm from using the 12-month grace period to secure a patent is that patent law in many other countries do not have a grace period. Therefore, a publication in the U.S. is considered "prior art" and prevents a firm from getting a patent in many other countries.

by creating prior art that might stop rivals from patenting and obtaining the exclusive rights to use an invention.

The above discussion suggests firms without adequate resources are more likely to benefit from scientific publication post AIA. In Section 2 we also demonstrate that AIA increases the effectiveness of pre-emptive publication strategy for a lagging firm. This leads to our first hypothesis:[3]

H1: Relative to firms with adequate resources, firms with financial constraints are more likely to increase scientific publications in response to an increase in technological competition.

3.2 Cross-sectional determinants of technological competition on disclosure decisions

3.2.1 Capital Intensity

Commercialization of a firm's R&D outputs requires technology-specific capital investment. Such capital investment is sunk costs for the focal firm but creates barriers for competitors to enter the same product market. For example, the proprietary costs for Boeing to publish its new technology on jet engines are arguably lower than the costs for Microsoft to disclose a new software: it is unlikely that a competitor could quickly assemble an airplane product line to commercialize a similar technology related to Boeing engine technology after Boeing's publication. Thus, firms with a lower level of capital intensity are more concerned

[3] Arguably, firms with sufficient resources could also use strategic disclosure to pre-empt the preemptive strategy. However, Parchomovsky (2000) discusses several reasons why it is not an optimal strategy for firms with adequate resources to publish their research findings. First, early publication forces the firm to file a patent within a year, otherwise it becomes prior art and negatively affects the patentability of an invention. Second, even if the firm can file a patent application within the grace period, the inventor can never be certain of receiving the patent. In the meanwhile, publication already divests them of IP protection and reveals secrecy to rival firms. Therefore, publication is generally not a profit maximizing strategy for a firm that is ahead of the patent race.

about the increased technological competition post-AIA and thus will increase their scientific disclosures more. This leads to our second hypothesis:

H2a: The relation between financial constraints and technological competition-induced corporate scientific publications is more positive among firms with lower capital intensity.

3.2.2 Patent Competition

Firms innovate in different spaces to get monopoly power. The closer the focal firm's technology is to the mainstream on the product market, the more similar are the targeted customers; thus the higher the competition would be (Callander and Matouschek, 2022). Such competition causes firms to rely more on patent protection of their inventions from potential imitations. Furthermore, the overlap between a focal firms' innovation space and its competitors' space determines the intensity of patent race: a larger overlap potentially increases the likelihood that two firms will innovate on the same technology and compete for the same patent. Thus, we hypothesize that firms with more overlapped innovation space will respond more to the increased technological competition post-AIA and increase their scientific publications more significantly. The third hypothesis is as below:

H2b: The relation between financial constraints and technological competition-induced corporate scientific publications is more positive among firms with higher patent competition.

3.2.3 Patent Lifecycle

Bilir (2014) documents that firms are sensitive to foreign intellectual property protections when expanding their multinational business, but only for sectors with relatively long patent lifecycles. The reason is that for patents with relatively long lifecycles, the firm needs to secure the monopoly power for a relatively long period. Detailed scientific disclosure could potentially lead to imitation from competitors before the technology becomes obsolete and harm the commercial value of the invention. In contrast, for patents with relatively short lifecycles, it is unlikely that competitors would succeed in imitating the technology and launch similar products in the short run. Thus, we predict that firms with relatively long patent lifecycles will respond more to the increased technological competition of the AIA by increasing their scientific publications, which leads to our last hypothesis:

H2c: The relation between financial constraints and technological competition-induced corporate scientific publications is more positive among firms with longer patent lifecycles.

4. Empirical Methodologies

4.1 Data and Sample Selection

Our sample begins with all Compustat firm-year records from 2009 to 2015 with non-missing scientific publication information from Arora et al. (2021).[4] Arora et al. (2021) match academic articles covered in the "Science Citation Index" and "Conference Proceedings Citation Index-Science" with Compustat firms based on authors' affiliation.[5] We further exclude companies from the financial industry (SIC 6000-6999). We also obtain patent abstract

[4] We thank Arora et al. (2021) for kindly sharing their data on corporate scientific publications and patents information: https://zenodo.org/record/4320782#.YhKskOjMKUk. Arora et al. (2021) panel sample includes Compustat 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 publication over the sample period.
[5] "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).

information from PatentsView database. The final sample contains 7,952 firm-year observations from 1,457 unique firms.

4.2 Key Measure for Financial Constraints and Summary Statistics

We measure financial constraint using financial leverage for the following reasons. First, there is abundant evidence that a firm's financial leverage is a key determinant of financial constraint (Hadlock and Pierce, 2010; Kaplan and Zingales, 1997; Whited and Wu, 2006). Such leverage-introduced financial constraints are especially prominent for R&D-related investments because of the lack of collateral values (Brown et al., 2012). Anecdotes suggest that firms without adequate resources to quickly evaluate and commercialize their ideas are at a larger disadvantage in the patent race post-AIA.

Second, the debt overhang theory of Myers (1977) predicts that higher leverage increases the probability of a firm forgoing positive NPV projects in the future, because the investment income first goes to fulfil debt obligations. As a result, in some states, the payoff from these investments to shareholder is lower than the initial investment shareholders have to outlay. Thus, the debt overhang problem suggests that high financial leverage could distort firms' investment as shareholders may find it optimal to cut discretionary investments. The investment distortion delays the commercialization of R&D and arguably increases the proprietary cost of innovation disclosures. Furthermore, highly leveraged firms are more prone to litigation costs as litigation risk could amplify financial distress, and intellectual property-related litigation is costly.

Table 1 presents our summary statistics. **Panel A** shows that, an average firm in our sample publishes about 13 academic papers each year, with the most active firm publishing over 200 papers. Compared to Arora et al. (2021) sample, the average number of publications over our sample period (i.e. 2009 to 2015, the last 7 years of the sample in Arora et al., 2021) is low, consistent with the declining trend of scientific publications from the U.S. public firms over time. Compared with the Compustat universe, our sample firms tend to be smaller, more R&D intensive, less tangible, and less profitable.

Panel B of **Table 1** presents the summary statistics of sub-samples with high leverage and low leverage in the pre-AIA and post-AIA periods, separately. On average, corporate scientific publications increase significantly post-AIA for both firms with relatively high leverage and those with low leverage. We also note that high-leveraged firms are significantly different than low-leveraged firms in many dimensions including size, R&D expense, growth, tangibility, and performance (ROA and Loss) in pre- and post- periods, respectively. Therefore, it is important to control for these differences in our regressions.

Panel C of **Table 1** provides additional descriptive information of the sample by SIC 2-digit industries. Manufacturing industries (SIC codes 20-39), which include chemicals & allied products (SIC 28), electronic & other electric equipment (SIC 36) and instruments & related products (SIC 38), comprise the largest contributor of the sample observations. The average number of publications is relatively stable across different industries, with "Others" being the most active and "Transportation & Communications" being the least active.[6] The last three columns report the industry distribution of Compustat universe for the same sample period. Overall, the top four industries: manufacturing, service, transportation and communications, and mining together represent 88% of the Compustat universe. As compared with Compustat

[6] The high level of publications for "Others" industry is mainly driven by firm "GENERAL ELECTRIC CO".

universe, our sample is even more concentrated in these above four industries, making up 98% of our sample, with manufacturing industry alone accounting for 82% of the sample.

Table 2 shows the Pearson correlation among our key variables. On average, corporate scientific publications are negatively correlated with leverage ratio, positively correlated with firm size, growth, earnings performance, and firms' recent publication and patenting activities, but not correlated with R&D activities.

4.3 Regression Model

To test our main hypothesis, we adopt a DID design to compare changes in scientific publications by firms with high financial leverage (the treatment group) and firms with low financial leverage (the control group) before and after the enactment of the AIA. Specifically, we estimate the following regression model:

$$\begin{aligned} Ln(Pub)_{i,t} = {} & \beta_1 Leverage_{i,t} \times Post + \beta_2 XRD_{i,t} + \beta_3 Size_{i,t-1} + \beta_4 Growth_{i,t-t} + \beta_5 BM_{i,t-1} \\ & + \beta_6 Tangibility_{i,t-1} + \beta_7 ROA_{i,t-1} + \beta_8 Loss_{i,t-1} + \beta_9 CAPX_{i,t-1} \\ & + \beta_{10} Log(Pub\_Stock)_{i,t-1} + \beta_{11} Log(Patent\_Stock)_{i,t-1} \\ & + \beta_{12} R\&D\ Stock_{i,t-1} + Firm\ FE + Year\ FE + \epsilon_{i,t} \end{aligned}$$

Eq. (1)

where $Ln(Pub)_{i,t}$ is the natural logarithm of the number of academic articles firm *i* publishes during year *t*. $Post_{i,t}$ is an indicator variable that equals if the firm-year observation is during the 2013 to 2015 post-AIA period, and zero otherwise. $Leverage_{i,t}$ is the industry-adjusted book leverage averaged over the sample period for firm *i*.[7] We measure the leverage at the firm level by taking the average over the sample period to assure that the treatment measure is constant

[7] In untabulated results, we repeat the analyses based on an indicator variable that equals one if the firm leverage is higher than the sample median. Our results are robust to this alternative design.

before and after AIA. We follow prior literature and adjust the book leverage by subtracting the industry average to account for the cross-sectional differences in leverage across industries (Campello, 2006; Bernard, 2016).

We control for the contemporaneous R&D expense so that the publication is conditional on firm's R&D inputs. We also control for lagged R&D stock, patent stock, and publication stock to account for firms' historical R&D and publication activities. Other control variables include firm size (*Size*), growth (*Growth* and *BM*), capital intensity (*Tangibility* and *CAPX*), and operating performance (*ROA* and *Loss*). All variables are defined in Appendix A.

5. Empirical Results

5.1 Baseline Results

Table 3 presents the results for hypothesis 1. Columns (1) to (5) gradually add control variables and fixed effects; Column (5) presents the estimation results of Equation (1). First, the coefficients on *Post* dummy in Columns (1) to (3) are positive, suggesting that firms on average increase their scientific publications in the patent race post-AIA. Second, the coefficients on *Leverage×Post* are positive and significant at less than the 1% level. Consistent with hypothesis 1, highly leveraged firms increase their scientific publications more in response to the enhanced technological competition from the AIA. The magnitude of the coefficient (0.094) suggests that, relative to firms with low financial leverage (25^{th} percentile), firms with high financial leverage (75^{th} percentile) increase their scientific publications by 2.5% after the AIA. In Column (6), we add in Industry×Year fixed effects to address the concern that such finding is driven by industry-wide innovation cycles. In Column (7), we further control for the interactions between *Post* dummy and other control variables to address the concern that financial leverage is capturing other firm characteristics. The coefficients on *Leverage×Post* remain significantly positive and significant at the 5% and 10% levels, respectively.

5.2 Entropy balancing

An alternative to directly controlling for the systematic differences between treatment and control firms is entropy balancing. Entropy balancing is a matching technique that identifies weights for each control sample observation to equalize the distributions of underlying variables across treatment and control samples (Hainmueller, 2012; McMullin and Schonberger, 2020). Relative to propensity score matching, entropy matching has the advantage of controlling for variance in variables and ensures that higher-order moments of the covariate distribution are similar across treated and control samples. To implement the matching approach, we first transform the continuous treatment variable, *Leverage*, into a dummy variable. We create a dummy variable *HighLev* that equals one if *Leverage* is above the sample median, and zero otherwise.

As recommended by Hainmueller (2012) and McMullin and Schonberger (2021), we first use propensity score matching to identify and discard outliers.[8] We then implement entropy balancing on the trimmed sample. Results based on entropy balancing are presented in **Table 4**. In Column (1) of **Table 4**, we regress the treatment dummy, *HighLev*, on the control variables based on the re-weighted sample. The coefficients on all control variables are insignificant, confirming that the first moment is balanced between high-leverage firms and low-leverage firms. Columns (2) to (4) present the results of re-estimating Eq. (1) based on the entropy

[8] We use one-to-one propensity score matching without replacement and require common support.

balanced sample. In general, the results are consistent with the baseline test: the coefficient on *HighLev×Post* is significantly positive. The economic magnitude is even larger: compared to low-leverage firms, firms with high leverage increase their scientific publications by 7.7% more in the post-AIA period.

5.3 Parallel Trends before the AIA

To provide further evidence that the change in scientific publications is attributable to the implementation of AIA, in this section, we verify the "parallel trends" assumption of DID design. The "parallel trends" assumption requires the difference between the treatment group and the control group to be constant in the pre-AIA period. Thus, in the absence of events, the common trend will presumably continue in the post period.

We use two methods to verify the parallel trends in the pre-AIA period. First, we run a pseudo test based on the pre-AIA sample (i.e. 2009 to 2012). We create a pseudo-Post dummy that equals one for year 2011 and 2012, and zero for year 2009 and 2010. Then, we re-estimate Eq. (1) with the pseudo-Post dummy and the pre-AIA sample. Results are reported in **Table 5**. The coefficient on *Leverage×Post* is not significantly different from 0, supporting the parallel trends assumption.

Second, we follow prior literature and estimate the following regression:

$$\begin{aligned} Ln(Pub)_{i,t} = {} & \beta_1 Y10_{i,t} * Leverage_{i,t} + \beta_2 Y11_{i,t} * Leverage_{i,t} + \beta_3 Y12_{i,t} * Leverage_{i,t} \\ & + \beta_4 Y13_{i,t} * Leverage_{i,t} + \beta_5 Y14_{i,t} * Leverage_{i,t} + \beta_6 Y15_{i,t} * Leverage_{i,t} \\ & + \beta_7 Leverage_{i,t} + Controls + FEs + \epsilon_{i,t} \end{aligned}$$

Eq. (2)

where dummy variables *Y10* to *Y15* represent the fiscal year 2010 to 2015, separately. β_1 to β_6 captures the differential scientific publications of financial-leverage firms in year 2010 to 2015, with 2009 as the benchmark. We include the same set of control variables as in Eq. (1). The coefficients and 95% confidence intervals are plotted in Figure 2.

Panel A (Panel B) of **Figure 2** is based on the model with industry (firm) fixed effects and year fixed effects. First, the coefficients on $Y10_{i,t} \times Leverage_{i,t}$, $Y11_{i,t} \times Leverage_{i,t}$, and $Y12_{i,t} \times Leverage_{i,t}$ are not significantly different from 0, consistent with the parallel trends assumption. Second, **Figure 2** demonstrates that the effects of the AIA on scientific publications have gradually become predominant since 2013. One potential reason for the gradual reaction is that for a patent with part of its claimed invention from pre-AIA applications (i.e. revised applications), the patent application will still be subject to the pre-AIA rules. Thus, the implementation of AIA is gradual over time (Crouch, 2016).

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

5.4.1 Size and Tangibility (H2a)

Hypothesis 2a predicts that the effect of the AIA is stronger when a firm is less capital intensive, which is a proxy for the entrance cost of potential competitors. To examine the moderating effect of capital intensity, we split the sample based on three firm characteristics: (1) book asset, (2) property, plant, and equipment (PP&E), and (3) capital expenditure following prior literature (Li, 2010). Specifically, we measure each firm characteristic at the firm level by taking the average over the sample period for each firm. We then split the sample based on whether the capital intensity measures are above or below the sample median. Splitting the sample based on firm-level characteristics allows a firm to remain in a given subsample over the sample period. Within each subsample, we estimate Eq. (1) separately. Results are reported in **Table 6**. Consistent with hypothesis 2a, the effect of the AIA on firms' scientific publications concentrates among small firms, firms with low capital expenditure, and firms with low PP&E. In terms of economic significance, among firms with relatively small size, low PP&E, or low expenditure, scientific publications increase significantly by 3.4% to 4.1% post-AIA.

5.4.2 Patent Competition (H2b)

Firms that face more patent competition would experience larger impact from the patent race post-AIA (H2b). We measure patent competition in two ways. First, we measure the textual similarity between the focal firm's patent and the patents of its SIC 3-digit industry peers based on each patent abstract. Arts et al. (2017) validate that textual similarity captures the technological similarity. A higher level of patent similarity between a focal firm's patent portfolio and its industry peers' patent portfolio implies larger innovation space overlaps, and thus higher patent competition. Results of subsample analysis based on patent textual similarity are presented in Columns (1) and (2) of **Table 7**. Consistent with H2b, the effect of the AIA on firms' scientific publications concentrates among firms with high patent similarity. For firms with high patent similarity, one inter-quartile increase in financial leverage increases firms' scientific publications by 4.6%, while firms with low patent similarity do not experience a significant change in scientific publications after the AIA.

Second, Arora et al. (2021) find that firms whose scientific publications receive more citations from outside patents face higher proprietary costs. A higher level of citations from patents filed by outside firms suggests that a firm's published ideas receive larger interest from potential competitors. On average, the median number of citations a firm's publication receives is zero. So, we split the sample with zero as the threshold. We find weak evidence that financial-leverage firms who receive more citations increase their publications; for firms whose publications on average receive zero patent citations, the coefficient on *Leverage×Post* remains positive but insignificant.

5.4.3 Patent Lifecycle (H2c)

Innovations with relatively short lifecycles rely less on patent protection and thus are less subject to increased technological competition post-AIA. H2c predicts that the effect of AIA on scientific publications is stronger among firms with relatively long patent lifecycles. Following Bilir (2014), we measure the lifecycle of a patent by the length of the period during which a patent continues to be cited by follow-up patents. A longer citation duration implies that the patented invention remains active in the field for a longer period. Specifically, for each patent, we calculate the 99^{th} percentile of the gaps between the focal patent grant date and the application date of follow-up patents that cite the focal patent. I then measure the average patent lifecycle at both firm-level (Columns 1 and 2) and SIC 3-digit level (Columns 3 and 4). Subsample analysis results are presented in **Table 8**. Consistent with H2c, firms with relatively long patent lifecycles respond significantly to the AIA by increasing their scientific publications. Conditional on long-lifecycle, one inter-quartile increase in financial leverage will increase firms' scientific publications by 1.98% to 5.95% post-AIA. In contrast, for firms with a relatively short patent lifecycle, scientific publications increase is insignificant in the post AIA period.

6. Robustness tests and additional analyses

6.1 Robustness tests

We use alternative measures for financial constraints to ensure that our results are not driven by a particular measure. In the first scheme, we employ two alternative leverage ratio measures: (1) the industry-adjusted book leverage of the firm net of cash holdings (Bernard, 2016); this measure accounts for prior evidence that cash holdings reduce the firm's financial constraint by deducting cash holdings from the total debt of the firm; (2) market leverage ratio (defined as the sum of short- and long-term debt divided by the sum of the market value of shareholders' equity, short-term debt and long-term debt). In the second scheme, we use two popular measures for firms' external financing constraints: the Kaplan-Zingales (KZ) index (Kaplan and Zingales, 1997) and the Whited-Wu (WW) index (Whited and Wu, 2006). We use the industry-adjusted KZ and WW index measures to be consistent with our main specification.

As shown in **Table 9**, the results mirror our baseline results. In particular, the coefficient on the interaction term: *Constraint* × *Post* is positive and statistically significant in the majority of regressions, with the exception of the WW index.

6.2 Effectiveness of Strategic Scientific Publications post-AIA

In this section, we further investigate the effectiveness of strategic scientific publications in the post-AIA patent race. As discussed in section 2, scientific publications, on the one hand, give the publishing firm a 12-month grace period to secure the patent application right in advance. On the other hand, firms can defensively disclose an invention so that competitors would not be able to patent it. To empirically examine whether scientific publications help firms achieve such strategic IP protection goals, we estimate the following two regressions:

$$
\begin{aligned}
Ln(OwnPatentApp)_{i,t} \\
&= \beta_1 Ln(Pub)_{i,t-1} \times Post + \beta_2 Post + \beta_3 Ln(Pub)_{i,t-1} + Controls + Firm\ FE \\
&+ Year\ FE + \epsilon_{i,t}
\end{aligned}
$$

Eq. (*3a*)

$$Ln(PeerPatentGrt)_{i,\{t,t+1\}} = \beta_1 Ln(Pub)_{i,t-1} \times Post + \beta_2 Post + \beta_3 Ln(Pub)_{i,t-1} + Controls\ + Firm\ FE + Year\ FE + \epsilon_{i,t}$$

Eq. (*3b*)

The dependent variable in Eq. (3a) is the natural logarithm of one plus the number of focal firms' patents applications in years t. The variable of interest is the interaction between the number of scientific publications in year t-1 for the focal firm: $Ln(pub)_{i,t-1}$ and $Post$ dummy. If firms increase publications to take advantage of the one-year grace period to secure a patent, we would expect their patent applications within one year following the publication to increase. In contrast, if the increased publications are because a firm anticipates itself to lose the patent race and thus make the invention public knowledge to block rivals' patenting, we would expect the focal firm's patent application to decrease following publications. Estimation results of Eq. (3a) are presented in Columns (1) and (2) of **Table 10**. We find that the coefficient on $Post$ is negative, suggesting focal firms' patent applications following publications within a year decrease post-AIA. The evidence is consistent with pre-emptive publication strategies instead of publishing to secure a patent.

We further examine whether firms' pre-emptive publication strategy is effective in blocking competitors' from receiving a patent. In Eq. (3b), we use the log average number of SIC 3-digit industry peers' patents granted in years t and t+1 as the dependent variable. We use two years because prior literature shows that on average a patent takes two years to get approved (e.g., Saidi and Zaldokas, 2021). Columns (3) and (4) of **Table 10** report the results of this exercise. In Columns (3) and (4), the coefficients on $Ln(Pub)_{i,t-1} \times Post$ are significantly negative, supporting the effectiveness of defensive publication strategies. Overall, the evidence is consistent with firms increasingly using scientific publications to deter competitors from patenting an invention post-AIA, rather than to take advantage of the grace period to delay patent application.

7. Conclusion

A first-to-file system under the Leahy-Smith America Invents Act of 2011 is generally thought to induce a race to the patent office. In this race, corporations with sufficient resources and skilled attorneys on staff can help quickly gather resources to file a patent. In contrast, firms with limited recourse are disadvantaged.[9] We conjecture and find that firms with less financial resource strategically increase their scientific publications in academic journals after the enactment of AIA as a strategy to raise the patentability threshold for rivals in the accelerated patent race. The intuition is that for a lagging firm, having an invention in the public domain is preferrable than having it in the hands of a competitor.

We document three firm characteristics, in addition to financial leverage, that further intensify firms' strategic disclosure through scientific publications after the AIA. First, we find that a firm increases its scientific publications more significantly when the firm is smaller or less capital intensive so that a competitor has lower entrance cost. Second, we find the increase in scientific publications is more prominent among firms that face more intensive patent competition. Lastly, firms whose inventions have longer lifecycles also increase their publications more since IP protection is more important for them.

[9] Using Canadian data, Abrams and Wagner (2013) find that a shift to a first-to-file system from a first-to invent system results in a substantial reduction in patenting by individual inventors compared to firms.

One concern with our results is that fundamental differences between firms with high and low leverage ratios lead to observed changes in their scientific publication around AIA. We include numerous control variables and use entropy balancing to alleviate this concern. Our cross-sectional tests also raise the hurdle for an alternative explanation. Nevertheless, we acknowledge that we cannot completely rule out the possibility that unidentified firm characteristics impact our inferences.

Overall, this paper presents consistent evidence that technological competition is an important determinant of corporate scientific publications. Corporate scientific publications are of increasing interest to researchers, because they convey early signals of firms' growth potential. Academic publications also have unique functions in the knowledge-based economy, such as the contribution to reciprocity (Shen, 2021). By weakening protection on firms' R&D secrecy and accelerating patent race, the AIA significantly increases corporate scientific publications. Such a consequence, unexpectedly, is consistent with the regulator's goal to promote the dissemination of innovation-based knowledge for social benefits. By encouraging inventors to accelerate their patent applications, the AIA is designed to push technical knowledge to enter the patent disclosure system. The finding that knowledge dissemination through scientific publications also increases post-AIA should be of great interest to regulators.

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Figure 1. Timeline of the AIA

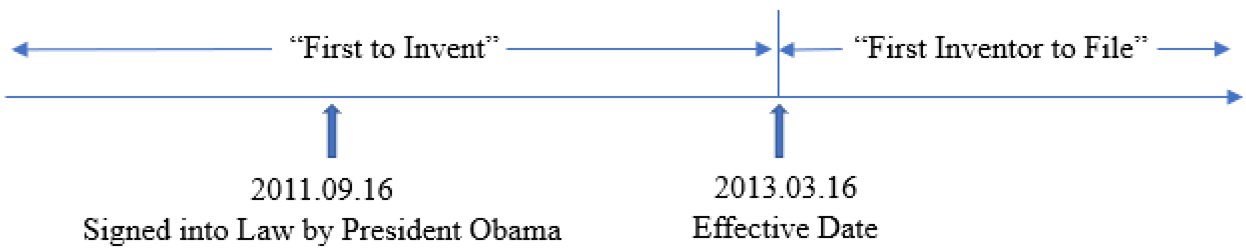


Figure 2. The Effect of the AIA

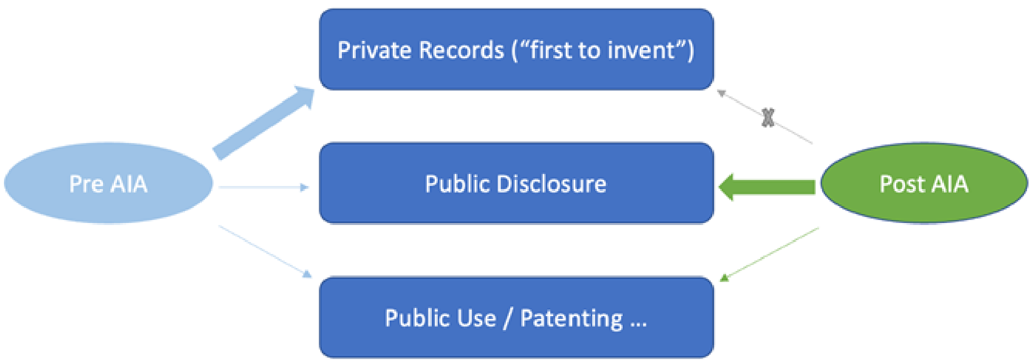
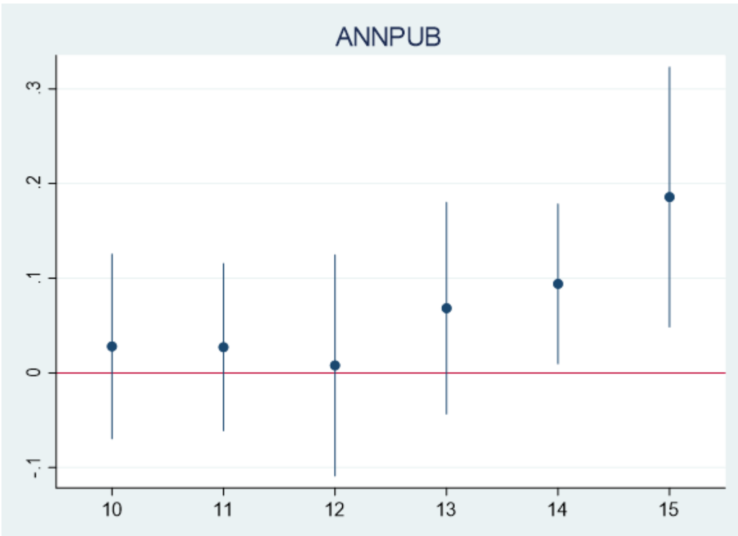


Figure 3. Parallel Trend Analysis

Panel A. Industry and Time Fixed Effects



Panel B. Firm and Time Fixed Effects

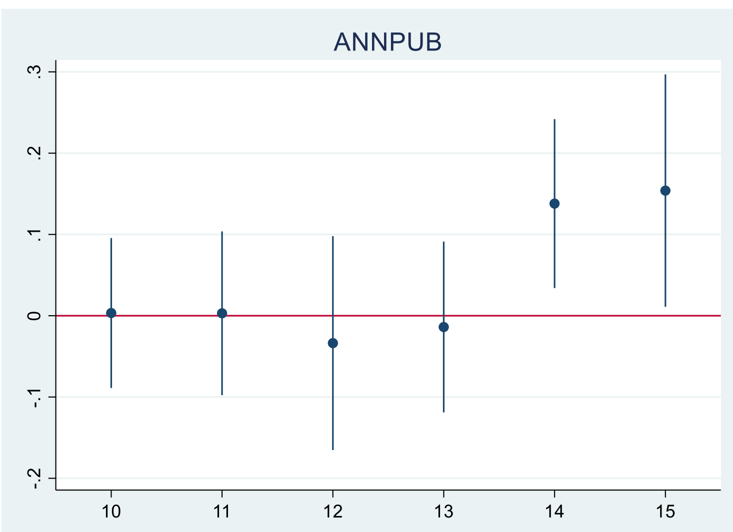


Table 1: Summary Statistics

Panel A: Full Sample

VARIABLES	N	Mean	SD	Min	P25	Median	P75	Max	Compustat	
									N	Mean
Pub	7,952	1.245	1.418	0.000	0.000	0.693	2.079	5.365		
Pub(unlogged)	7,952	12.729	34.779	0.000	0.000	1.000	7.000	212.867		
Leverage	7,952	-0.181	0.346	-1.321	-0.261	-0.123	0.006	0.985	23,731	-0.478
R&D Expense	7,952	0.140	0.200	0.000	0.019	0.066	0.164	1.044	23,731	0.049
Size	7,951	6.025	2.438	0.753	4.311	6.010	7.883	11.148	23,731	6.537
Growth	7,764	0.056	0.358	-1.156	-0.065	0.054	0.174	1.320	23,731	0.076
R&D Stock	7,951	0.444	0.706	0.000	0.056	0.190	0.490	4.602	23,731	0.141
CAPX	7,941	0.032	0.031	0.000	0.012	0.023	0.042	0.168	23,731	0.054
BM	7,774	0.805	0.553	0.083	0.399	0.695	1.081	3.369	23,731	0.976
Tangibility	7,951	0.153	0.135	0.002	0.052	0.113	0.213	0.596	23,731	0.280
ROA	7,941	-0.073	0.441	-2.447	-0.082	0.086	0.145	0.316	23,731	0.061
Loss	7,952	0.436	0.496	0.000	0.000	0.000	1.000	1.000	23,731	0.328
Log(Pub_Stock)	7,792	2.373	1.790	0.000	0.900	2.046	3.520	7.164		
Pub_Stock(unlogged)	7,792	67.886	193.223	0.000	1.459	6.733	32.770	1291.497		
Log(Patent_Stock)	7,792	3.201	1.955	0.178	1.641	2.961	4.550	8.088		
Patent_Stock(unlogged)	7,792	167.342	439.555	0.195	4.159	18.325	93.612	3253.700		
OwnPatent	6,526	2.499	1.950	0.000	0.693	2.303	3.871	5.220		
PeerPatent	6,158	4.077	1.078	2.853	3.452	4.047	5.025	5.428		

Panel B: Summary Statistics by Subsamples

	Subsample Summary Statistics				**Subsample Difference**			
	Low Leverage		High Leverage		LowLev	HighLev	Pre	Post
	Pre	Post	Pre	Post	Post-Pre	Post-Pre	High-Low	High-Low
Pub	1.222	1.321	1.152	1.343	0.099*	0.191***	-0.070	0.022
Pub(unlogged)	11.098	14.324	11.599	15.302	3.225**	3.703**	0.501	0.979
Leverage	-0.417	-0.439	0.070	0.055	-0.021*	-0.015*	0.487***	0.494***
R&D Expense	0.186	0.186	0.097	0.088	-0.001	-0.009	-0.089***	-0.098***
Size	5.212	5.450	6.591	6.976	0.238***	0.385***	1.379***	1.526***
Growth	0.075	0.073	0.039	0.038	-0.002	-0.001	-0.036***	-0.035**
BM	0.816	0.613	0.955	0.751	-0.203***	-0.205***	0.139***	0.138***
Tangibility	0.119	0.109	0.196	0.185	-0.011**	-0.011*	0.077***	0.077***
ROA	-0.118	-0.119	-0.031	-0.021	-0.001	0.011	0.087***	0.098***
Loss	0.507	0.511	0.382	0.334	0.004	-0.048**	-0.125***	-0.177***
CAPX	0.028	0.027	0.037	0.037	-0.000	-0.000	0.009***	0.009***
Pub_Stock	2.309	2.427	2.330	2.479	0.118*	0.149*	0.021	0.052
Patent_Stock	2.730	2.967	3.438	3.771	0.237***	0.333***	0.708***	0.804***
R&D Stock	0.614	0.539	0.328	0.269	-0.075***	-0.059**	-0.286***	-0.270***
Pub_Stock(unlogged)	55.438	69.889	66.361	86.601	14.451*	20.241**	10.922*	16.712*
Patent_Stock(unlogged)	83.535	122.350	189.043	303.706	38.815***	114.663***	105.508***	181.355***
OwnPatent	2.134	2.319	2.704	3.020	0.185**	0.316***	0.570***	0.701***
PeerPatent	3.984	4.264	3.969	4.335	0.280***	0.366***	-0.016	0.071

Panel C: Distribution by Industry

SIC Code	Industry	Firm_Years	Firms	Mean_Pub(unlogged)	Compustat Firm_Years	Compustat Firms
01-09	Agriculture, Forestry and Fishing	12	3	73.707	95	21
10-14	Mining	107	20	20.653	1,797	385
15-17	Construction	16	3	1.927	326	63
20-39	Manufacturing	6,553	1,221	12.714	11,355	2,294
40-49	Transportation and Communications	151	29	6.163	2,988	582
50-51	Wholesale Trade	66	13	16.853	825	177
52-59	Retail Trade	23	4	8.627	1,586	319
70-89	Services	1,014	213	11.112	4,708	1,087
99	Others	10	3	127.177	51	11

This table provides the descriptive information of our sample and key variables. Panel A reports the distribution of the variables in our main tests, as well as the mean values based on Compustat universe over the same sample period (2009 to 2015). Panel B reports the mean values in high-leverage, low-leverage, pre-AIA, and post-AIA subsamples, separately, and the t-test between every two subsamples. Panel C reports the industry distribution of our sample, as well as the industry distribution of the Compustat universe over our sample period. All variables are defined in Appendix.

Table 2: Pearson Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Pub	1.00														
(2) OwnPatent	**0.58**	1.00													
(3) PeerPatent	-0.01	**0.23**	1.00												
(4) Leverage	**-0.17**	**0.11**	**0.17**	1.00											
(5) Post	**0.05**	**0.06**	**0.14**	**-0.04**	1.00										
(6) R&D Expense	0.01	**-0.15**	**-0.08**	**-0.20**	-0.01	1.00									
(7) Size	**0.46**	**0.66**	**0.13**	**0.16**	**0.06**	**-0.51**	1.00								
(8) Growth	**0.02**	0.00	0.00	**-0.06**	0.00	-0.01	0.01	1.00							
(9) BM	**-0.14**	**-0.05**	**0.05**	**0.10**	**-0.18**	**-0.29**	**0.13**	**-0.17**	1.00						
(10) Tangibility	0.00	**0.03**	**-0.11**	**0.25**	**-0.04**	**-0.26**	**0.26**	**-0.04**	**0.18**	1.00					
(11) ROA	**0.10**	**0.30**	**0.16**	**0.05**	0.00	**-0.65**	**0.61**	**0.07**	**0.22**	**0.17**	1.00				
(12) Loss	**-0.12**	**-0.27**	**-0.11**	**-0.13**	**-0.02**	**0.45**	**-0.53**	**-0.09**	**0.04**	**-0.14**	**-0.54**	1.00			
(13) CAPX	0.00	**0.05**	0.00	**0.18**	0.00	**-0.14**	**0.17**	**0.06**	**0.02**	**0.65**	**0.12**	**-0.10**	1.00		
(14) Pub_Stock	**0.88**	**0.59**	-0.01	**-0.15**	**0.04**	0.01	**0.46**	-0.02	**-0.12**	**0.03**	**0.10**	**-0.12**	-0.01	1.00	
(15) Patent_Stock	**0.56**	**0.90**	**0.20**	**0.14**	**0.07**	**-0.18**	**0.66**	**-0.05**	0.00	**0.08**	**0.30**	**-0.28**	**0.06**	**0.63**	1.00
(16) R&D Stock	-0.01	**-0.18**	**-0.11**	**-0.16**	**-0.04**	**0.78**	**-0.55**	**-0.04**	**-0.27**	**-0.21**	**-0.79**	**0.43**	**-0.14**	0.02	**-0.18**

This table reports the Pearson covariance matrix among the variables of our main tests. Correlations in bold are statistically significant at 10% level.

Table 3: AIA and Scientific Publications

VARIABLES	(1) Pub_t	(2) Pub_t	(3) Pub_t	(4) Pub_t	(5) Pub_t	(6) Pub_t	(7) Pub_t
$Leverage_t$×Post	**0.125*** **	**0.119*** **	**0.097*** **	**0.100*** **	**0.094*** **	**0.120** **	**0.152* **
	(0.038)	**(0.037)**	**(0.029)**	**(0.033)**	**(0.034)**	**(0.046)**	**(0.084)**
$Leverage_t$	-0.723***	-0.738***	-0.237***	-0.109***	-	-0.112***	-0.128***
	(0.196)	(0.190)	(0.038)	(0.037)	-	(0.040)	(0.045)
Post	0.151***	0.149***	0.025	-	-	-	-
	(0.024)	(0.023)	(0.025)	-	-	-	-
R&D $Expense_t$		-0.148	0.487***	0.467***	0.087*	0.468***	0.531***
		(0.164)	(0.078)	(0.071)	(0.052)	(0.074)	(0.056)
$Size_{t-1}$			0.107***	0.132***	0.261***	0.133***	0.115***
			(0.020)	(0.025)	(0.030)	(0.026)	(0.020)
$Growth_{t-1}$			0.108***	0.092***	0.014	0.097***	0.086***
			(0.017)	(0.017)	(0.025)	(0.017)	(0.017)
BM_{t-1}			-0.090**	-0.063	-0.017	-0.067	-0.042
			(0.044)	(0.041)	(0.024)	(0.043)	(0.033)
$Tangibility_{t-1}$			-0.586***	-0.145	0.239	-0.179	-0.200*
			(0.112)	(0.118)	(0.261)	(0.123)	(0.107)
ROA_{t-1}			-0.182***	-0.185***	-0.097***	-0.186***	-0.213***
			(0.043)	(0.036)	(0.036)	(0.038)	(0.055)
$Loss_{t-1}$			0.082	0.056	0.032	0.059	0.032
			(0.050)	(0.051)	(0.020)	(0.055)	(0.042)
$CAPX_{t-1}$			1.699***	1.037**	-0.034	1.158**	1.369***
			(0.416)	(0.433)	(0.520)	(0.461)	(0.368)
Pub_Stock_{t-1}			0.657***	0.632***	-0.057	0.637***	0.643***
			(0.011)	(0.016)	(0.036)	(0.016)	(0.017)
$Patent\_Stock_{t-1}$			-0.036***	-0.036***	0.080**	-0.038***	-0.037***
			(0.009)	(0.012)	(0.038)	(0.012)	(0.012)
R&D $Stock_{t-1}$			-0.146***	-0.151***	0.096***	-0.153***	-0.170***
			(0.021)	(0.025)	(0.037)	(0.026)	(0.030)
Constant	1.063***	1.081***	-0.839***	-0.955***	-0.559***	-0.951***	-0.938***
	(0.062)	(0.062)	(0.090)	(0.117)	(0.190)	(0.118)	(0.113)
Observations	7,952	7,952	7,551	7,542	7,442	7,228	7,228
R-squared	0.030	0.030	0.789	0.804	0.922	0.810	0.811
Control×Post	No	No	No	No	No	No	Yes
Industry FE	No	No	No	Yes	No	No	No
Firm FE	No	No	No	No	Yes	No	No
Year FE	No	No	No	Yes	Yes	No	No
Industry×Year FE	No	No	No	No	No	Yes	Yes

This table presents the regression results of our main tests on the impact of the AIA on corporate scientific publications. All continuous variables are winsorized at the top and bottom 2.5%. The standard errors reported in parentheses are clustered at SIC 3-digit industry level. *,**,*** indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 4: PSM and Entropy Balancing

VARIABLES	(1) $HighLev_t$	(2) Pub_t	(3) Pub_t	(4) Pub_t
$HighLev_t$×Post		**0.097***** **(0.036)**	**0.079**** **(0.034)**	**0.077*** **(0.040)**
Post		-0.072* (0.042)	- -	- -
$HighLev_t$		-0.054 (0.053)	0.016 (0.044)	- -
R&D $Expense_t$	-0.088 (0.124)	0.547*** (0.115)	0.511*** (0.106)	0.184 (0.149)
$Size_{t-1}$	0.021 (0.021)	0.076*** (0.018)	0.105*** (0.022)	0.220*** (0.043)
$Growth_{t-1}$	-0.011 (0.023)	0.086*** (0.023)	0.066*** (0.020)	-0.013 (0.028)
BM_{t-1}	-0.007 (0.030)	-0.085** (0.040)	-0.044 (0.035)	-0.006 (0.038)
$Tangibility_{t-1}$	-0.074 (0.224)	-0.417** (0.207)	-0.038 (0.199)	0.013 (0.260)
ROA_{t-1}	-0.047 (0.078)	-0.254*** (0.074)	-0.292*** (0.069)	-0.076 (0.086)
$Loss_{t-1}$	0.058 (0.040)	0.029 (0.035)	0.002 (0.031)	0.019 (0.040)
$CAPX_{t-1}$	-0.343 (0.706)	1.223*** (0.457)	1.217** (0.465)	0.882 (0.540)
Pub_Stock_{t-1}	-0.003 (0.039)	0.642*** (0.022)	0.603*** (0.024)	-0.112* (0.060)
$Patent\_Stock_{t-1}$	-0.009 (0.033)	-0.011 (0.016)	0.009 (0.024)	0.113*** (0.043)
R&D $Stock_{t-1}$	0.011 (0.047)	-0.239*** (0.037)	-0.243*** (0.041)	0.020 (0.042)
Constant	0.410*** (0.131)	-0.599*** (0.089)	-0.870*** (0.113)	-0.320 (0.280)
Observations	4,187	4,187	4,180	4,135
R-squared	0.006	0.778	0.800	0.916
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes
Year FE	No	No	Yes	Yes

This table presents the entropy balancing regression results of our main tests. Column 1 reports the regression of high leverage dummy on matched firm characteristics. Column 2 to 4 report the results of our main test based on propensity score matching and entropy balancing. All continuous variables are winsorized at the top and bottom 2.5%. The standard errors reported in parentheses are clustered at SIC 3-digit industry level. *,**,*** indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 5: Pseudo Test

VARIABLES	(1) Pub_t	(2) Pub_t	(3) Pub_t	(4) Pub_t
$Leverage_t$×Post	**-0.103**	**-0.004**	**0.005**	**-0.083**
	(0.072)	**(0.041)**	**(0.041)**	**(0.054)**
$Leverage_t$	-0.675***	-0.233***	-0.130**	-
	(0.168)	(0.043)	(0.053)	-
Post	0.017	-0.044**	-	-
	(0.016)	(0.018)	-	-
Observations	4,779	4,519	4,512	4,387
R-squared	0.033	0.787	0.804	0.940
Controls	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes
Year FE	No	No	Yes	Yes

This table presents the regression results of a pseudo test based on the pre-AIA period (2009 to 2012) and 2010 as the pseudo event time. All continuous variables are winsorized at the top and bottom 2.5%. The standard errors reported in parentheses are clustered at SIC 3-digit industry level. *,**,*** indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 6: Subsample Analysis - Capital Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	Size		CAPX		PPE	
VARIABLES	Low	High	Low	High	Low	High
Leverage$_t$×Post	**0.121*****	**-0.123**	**0.157*****	**-0.033**	**0.126****	**0.032**
	(0.044)	**(0.121)**	**(0.059)**	**(0.094)**	**(0.055)**	**(0.082)**
Low - High	0.244*		0.190*		0.094	
P-value	(1.882)		(1.703)		(0.956)	
Observations	3,584	3,858	3,629	3,813	3,599	3,843
R-squared	0.834	0.942	0.926	0.918	0.919	0.925
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the subsample analyses based on size (Column 1 and 2), capital expenditure (Column 3 and 4), and property, plant, and equipment (Column 5 and 6). All continuous variables are winsorized at the top and bottom 2.5%. The standard errors reported in parentheses are clustered at SIC 3-digit industry level. *,**,*** indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 7: Subsample Analysis - Patent Competition

	(1)	(2)	(3)	(4)
	Patent Similarity		Outside Citation	
VARIABLES	Low	High	Low	High
Leverage$_t$×Post	**-0.026**	**0.171*** **	**0.065**	**0.107***
	(0.084)	**(0.062)**	**(0.046)**	**(0.054)**
Low - High	-0.197*		-0.042	
t-stat	(-1.891)		(-0.587)	
Observations	3,029	2,881	4,051	3,391
R-squared	0.939	0.849	0.772	0.930
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table presents the subsample analyses based on patent competition. In Column 1 and 2 we measure patent competition as the textual similarity between the focal firm's patents and the patents of industry peers based on patent abstracts. In Column 3 and 4 we measure patent competition as the number of citations focal firm's publications receive from outside patents. All continuous variables are winsorized at the top and bottom 2.5%. The standard errors reported in parentheses are clustered at SIC 3-digit industry level. *,**,*** indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 8: Subsample Analysis - Patent Lifecycle

	(1)	(2)	(3)	(4)
	Firm-Level		Industry-Level	
VARIABLES	Short	Long	Short	Long
Leverage$_t$×Post	**0.060**	**0.223*****	**0.111**	**0.074****
	(0.086)	**(0.063)**	**(0.104)**	**(0.033)**
Short - Long	-0.164		0.037	
t-stat	(-1.542)		(0.340)	
Observations	2,951	2,938	3,950	3,363
R-squared	0.939	0.898	0.929	0.916
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table presents the subsample analyses based on patent lifecycles. We measure patent lifecycles based on the length of the period over which a patent keeps been cited by follow-up patents. In Column 1 and 2 we measure the patent lifecycle at firm level, while in Column 3 and 4 we measure the patent lifecycle at the SIC 3-digit industry level. All continuous variables are winsorized at the top and bottom 2.5%. The standard errors reported in parentheses are clustered at SIC 3-digit industry level. *,**,*** indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 9: Alternative Measures of Financial Leverage and Constraints

VARIABLES	(1) Market Leverage	(2) Net Leverage	(3) KZ Index	(4) WW Index
$Measure_t$×Post	**0.245****	**0.105*****	**0.001*****	**-0.034**
	(0.122)	**(0.031)**	**(0.000)**	**(0.043)**
Observations	7,442	7,442	7,222	7,203
R-squared	0.922	0.922	0.920	0.922
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table presents the regression results of our main tests on the impact of the AIA on corporate scientific publications, based on alternative measures of financial leverage or financial constraints. Alternative measures are defined in Appendix. All continuous variables are winsorized at the top and bottom 2.5%. The standard errors reported in parentheses are clustered at SIC 3-digit industry level. *,**,*** indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 10: Scientific Publications and Future Patents

VARIABLES	(1) $OwnPatentApp_t$	(2) $OwnPatentApp_t$	(3) $PeerPatentGrt_{\{t,t+1\}}$	(4) $PeerPatentGrt_{\{t,t+1\}}$
$Publication_{t-1}$×Post	-0.064***	-0.071***	-0.038**	-0.025**
	(0.018)	(0.013)	(0.015)	(0.013)
$Publication_{t-1}$	0.455***	0.035	0.019	0.000
	(0.041)	(0.022)	(0.048)	(0.013)
Post	-0.234***		0.371***	
	(0.029)		(0.057)	
$Size_{t-1}$	0.150***	0.107***	-0.017	-0.037
	(0.019)	(0.036)	(0.057)	(0.031)
$Growth_{t-1}$	0.127***	-0.010	-0.012	0.026**
	(0.037)	(0.019)	(0.038)	(0.011)
BM_{t-1}	-0.214***	-0.024	0.140**	0.016
	(0.036)	(0.025)	(0.063)	(0.021)
$Tangibility_{t-1}$	-0.788***	0.308	-1.924**	-0.140
	(0.216)	(0.206)	(0.920)	(0.227)
ROA_{t-1}	-0.227***	-0.093*	0.327*	0.042
	(0.065)	(0.050)	(0.196)	(0.036)
$Loss_{t-1}$	-0.028	-0.042*	-0.073	-0.014
	(0.036)	(0.024)	(0.066)	(0.017)
$CAPX_{t-1}$	2.715***	-0.492	4.259**	0.725*
	(0.523)	(0.429)	(1.715)	(0.376)
Pub_Stock_{t-1}	-0.303***	0.048	-0.125**	-0.008
	(0.021)	(0.067)	(0.056)	(0.034)
$Patent\_Stock_{t-1}$	0.613***	-0.186***	0.175**	0.047
	(0.016)	(0.053)	(0.067)	(0.032)
R&D $Stock_{t-1}$	-0.063	-0.033	0.081	0.028
	(0.046)	(0.027)	(0.088)	(0.018)
Constant	-0.755***	1.470***	3.858***	4.176***
	(0.084)	(0.251)	(0.285)	(0.155)
Observations	5,551	5,408	5,813	5,662
R-squared	0.731	0.949	0.127	0.930
Firm FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

This table presents the regression results on the impact of the AIA on the sensitivity of firms' patents, as well as their industry peers' patents on their past publications. Columns (1) and (2) use focal firm's patent applications in year t as the dependent variable. Columns (3) and (4) use the average of SIC 3-digit industry peers' patents as the dependent variable. All continuous variables are winsorized at the top and bottom 2.5%. The standard errors reported in parentheses are clustered at SIC 3-digit industry level. *,**,*** indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Appendix A: Variable Definitions

Variable Name	Definition
Pub	Natural logarithm of 1 plus the number of academic publications during year t.
Leverage	Firm-level average book leverage (Compustat items (DLTT + DLC) / AT) over the sample period, subtracting the SIC-3 digit industry median.
HighLev	Dummy variable that equals 1 if *Leverage* is above the sample median.
R&D Expense	R&D expenses scaled by total assets at the end of year t (Compustat items XRD / AT).
Size	Natural logarithm of total assets at the end of year t (Compustat item AT).
Growth	Natural logarithm difference of sales from year t-1 to t (Compustat item SALE).
CAPX	Capital expenditures scaled by total assets at the end of year t (Compustat items CAPX / AT).
BM	Book-to-market ratio at the end of year t (Compustat items AT / (PRCC_F*CSHO + DLTT + DLC)).
Tangibility	Net value of property, plants, and equipment scaled total assets at the end of year t (Compustat items PPENT /AT).
ROA	Operating income before depreciation scaled by total assets (Compustat items OIBDP / AT) at the end of year t.
Loss	Dummy variable that equals 1 if net income (Compustat item NI) is less than 0 at year t.
R&D Stock	Perpetual R&D stock based on a 20% annual depreciation rate, scaled by total assets. $\text{R\&D Stock}_t$ = ($\text{R\&D expense}_t$ + 0.8*$\text{R\&D expense}_{t-1}$ + 0.6*$\text{R\&D expense}_{t-2}$+ 0.4*$\text{R\&D expense}_{t-3}$+ 0.2*$\text{R\&D expense}_{t-4}$) / Asset_t.
Pub_Stock	Natural logarithm of 1 plus the perpetual stock of academic publications based on a 15% annual depreciation rate.
Patent_Stock	Natural logarithm of 1 plus the perpetual stock of patents based on a 15% annual depreciation rate.
OwnPatent	Natural logarithm of 1 plus the number of patents granted to the focal firm from year t to year t+1.
PeerPatent	Natural logarithm of the average number of patents granted to a firm's SIC 3-digit industry peers from year t to year t+1.
Market Leverage	Firm-level average market leverage (Compustat items (DLTT + DLC) / (PRCC_F*CSHO + DLTT + DLC)) over the sample period, subtracting the SIC 3-digit industry average.

Net Leverage	Firm-level average book leverage net of cash (Compustat items (DLTT + DLC - CHE) / AT) over the sample period, subtracting the SIC 3-digit industry average.
KZ Index	Firm-level average KZ (Kaplan and Zingales 1997) index (Compustat items -1.001909*(IB+DP)/PPENT + 0.2826389*(AT+PRCC_F*CSHO-CEQ-TXDB)/AT + 3.1319193*(DLTT+DLC)/(DLTT+DLC+SEQ) - 39.3678*(DVP+DVC)/PPENT - 1.314759*CHE/PPENT) over the sample period, subtracting the SIC 3-digit industry average.
WW Index	Firm-level average WW (Whited and Wu 2006) index (-0.091*(IB+DP)/Capital - 0.062*PosDiv + 0.021*DLTT/Capital - 0.044*log (Capital) + 0.102*Industry Sales Growth - 0.035*Sales Growth, where Capital is deflated by the replacement cost of total assets following Whited 1992, and PosDiv is a dummy variable that equals one for positive cash dividends), subtracting the SIC 3-digit industry average.