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ABSTRACT

We estimate the effect of patent protection on follow-on investments in corporate scientific research. We exploit a new method for identifying an exogenous reduction in the protection a granted patent provides. Using data on public, research-active firms between 1990 and 2015, we find that firms decrease follow-on research after a reduction in patent protection, as measured by a drop in internal citations to an associated scientific article. This effect is stronger for smaller firms and in industries where patents are traded less frequently. Our findings are consistent with a stylized model whereby patent protection is a strategic substitute for commercialization capability. Our results imply that stronger patents encourage follow-on research, but also shift the locus of research from big firms toward smaller firms and startups. As patent protection has strengthened since the mid-1980s, our results help explain why the American innovation ecosystem has undergone a growing division of innovative labor, where startups become primary sources of new ideas.

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1 Introduction

According to the National Science Foundation, firms account for 43% of U.S. investments in scientific research.[1] At least since Rosenberg (1990), scholars have sought to understand what motivates firms to invest in scientific research. Patent protection is one route, among many, that enables firms to secure their returns on scientific findings. In this paper we explore how changes in the level of patent protection affect investments in research, and how this effect varies across firms with different commercialization capabilities. If patents substitute for commercialization capability, firms lacking these capabilities will be more sensitive to changes in patent protection. Markets for technology enable firms to sell their inventions to others with superior commercialization capability, and hence would dampen the response to changes in patent protection. Our results indicate that patents are more valuable for firms who lack the ability to commercialize independently.

A large, influential literature has argued that firms can benefit from publishing research findings even if they never profit *directly* from commercializing the focal scientific discovery. Broadly speaking, this stream of research argues that firms invest in scientific research as a "ticket to the game" whereby the firm is able to absorb external knowledge (Cockburn & Henderson, 1998; Cohen & Levinthal, 1989; Rosenberg, 1990), attract talented researchers (Stern, 2004), and maintain a reputation with stakeholders or regulatory agencies (Azoulay, 2002; Hicks, 1995).[2] In this view, research investments are not sensitive to patent protection.

A parallel stream of research, and the point of departure for this paper, holds that firms may invest in scientific research in order to profit directly from innovation (Arora et al., 2021; Teece, 1986). The prospect of stronger patent protection would encourage research investment insofar as the inventions arising from their scientific discoveries can be patented, for example as *patent-paper pairs* (Murray & Stern, 2007). The value of patent protection in driving investments in scientific research could vary by firm characteristics, such as the ability to independently commercialize innovations. Teece (1986) suggested that patents can *substitute* for commercialization capabilities in appropriating value from innovation.

[1] National Science Foundation, National Center for Science and Engineering Statistics 2019. National Patterns of R&D Resources: 2017-18 Data Update. NSF 20-307. Available at https://ncses.nsf.gov/pubs/nsf20307

[2] Prior studies of the effectiveness of patents have focused on follow-on *patenting* by the inventing firm (Farre-Mensa et al., 2019; Galasso & Schankerman, 2018). However, less than one-quarter of patents reference the scientific literature (Marx & Fuegi, 2020a), and only 10% of research is patented (Belenzon & Schankerman, 2013). Studies that do examine the relationship between patent protection and the production of research (Murray & Stern, 2007; Sampat & Williams, 2019) typically do so by counting citations to a focal scientific article from *any* organization (sometimes entirely omitting "internal" citations to the firm's own research). Moser (2005) focuses not on patenting but the creation of underlying inventions. Arguably this is somewhat akin to scientific research. However, this analysis also focuses on general effects and not the firm's decision.

By excluding imitators, patents give inventors the time needed to develop the missing capabilities or facilitate technology licensing. In this formulation, patents are more important when firms lack relevant commercialization capabilities. On the other hand, large firms may have the expertise and experience to reduce the costs of information disclosure compared to small firms (Horstmann et al., 1985; Somaya et al., 2007), or the resources required to enforce their patents (Galasso et al., 2013; Lanjouw & Schankerman, 2004).

A natural question is whether patent protection and commercialization capability are more valuable when deployed together or separately. Put differently, the question is whether they are strategic substitutes or complements.[3] If patents and commercialization capabilities are complements, then strengthening patent rights would imply the locus of research and invention would shift toward bigger firms with greater commercialization capabilities.[4] Conversely, if they are substitutes, then stronger patents would shift the locus of research to smaller firms.

The empirical evidence on the substitutability vs. complementarity of protection and commercialization capability is decidedly mixed. Capponi et al. (2019), Clarkson and Toh (2010), Fischer and Henkel (2013), Hall et al. (2013), Leiponen and Byma (2009) and Mansfield (1986) all present evidence suggesting that patent protection and commercialization capability are complements. At the same time, Helfat (1994) and Cockburn and MacGarvie (2011) find support for substitutability.[5] These conflicting results, coupled with the fact that most empirical work on this topic is descriptive, makes it difficult to be confident about whether patents and commercialization capability are substitutes or complements.

As Teece (1986) implies, the relationship depends in part on whether the inventor can trade the invention in the market for technology to access the commercialization capability of the buyer. Because the buyer will have a greater commercialization capability, a sale can partially offset the impact of a reduction in patent protection if commercialization capability is a strategic substitute for patent protection. Conversely, if they are strategic complements, the buyer will value patents even more than the inventor, amplifying the impact of a loss of patent protection. Therefore, the ability to license or sell inventions will

[3]Formally, complementarity is defined in the context of supermodularity theory (Milgrom and Roberts, 1990; Milgrom and Roberts, 1995). When two activities (or assets) are strategic complements, the presence of the first increases the effect of the second on a given outcome. In the opposite case, the two activities are defined as strategic substitutes.

[4]Some commercialization capabilities may, however, be specific to research trajectories. Others, such as relationships with regulators, financiers, and suppliers; logistics and distribution; and manufacturing are typically broader in scope. Such capabilities are likely to be strongly correlated with firm size. In the discussion that follows, and in the empirical analysis, we will use firm size as a proxy for commercialization capability.

[5]Following Teece (1986), the innovation and management literature has explored the relationship between patents and other means of appropriating returns. For instance, Anton and Yao (2004) analyze the relationship between patents and secrecy. Others have examined the relationship in the context of bringing products to the market (e.g., Rothaermel and Hill (2005); Gans and Stern (2003)); licensing (Arora & Ceccagnoli, 2006; Cassiman & Veugelers, 2006), and acquisitions (Grimpe & Hussinger, 2014).

dampen the response under strategic substitutability, but amplify it under strategic complementarity.

Our approach is to assess whether the firm continues an existing program of research where patent protection is exogenously weakened. Following Murray and Stern (2007), we examine patent-paper pairs, i.e., where the firm obtains patent protection over a research discovery that is also published. Instead of comparing citation rates to the focal paper before vs. after the granting of a patent, we take advantage of an exogenous *de facto* reduction in the strength of patent protection due to the emergence of prior art *after the focal patent was granted.* Comparing the effect of such reduction to papers—in matched patent-paper pairs published by the same firm that did not experience such a reduction—allows us to infer whether the firm's continued investment in that program of research is affected by the sudden weakening of patent protection.

To distinguish patents that experience a *de facto* reduction in protection, we use a method first introduced by Lee (2020). The intuition is as follows. It is common for similar discoveries to happen independently at the same time (Bikard and Marx, 2019; Merton, 1961; Thompson and Kuhn, 2020).[6] Patent applications for similar inventions may be processed concurrently. Yet, patents with later priority dates may be granted *before* their prior art.[7] Thus, there are cases when patent grants are followed by the appearance of similar patents that count as prior art for the focal patent. When this happens, we argue that the *de facto* protection provided by the focal patents is reduced. We call these events "priority disclosures" and designate them as the treatment.

We confirm that the arrival of a closely related patent *before* the grant of the focal patent results in a reduction in scope of the focal patent, as indicated by an increase in the number of words in the principal independent claim (following Kuhn and Thompson (2019)). When the related patent arrives *after* the grant, the claims cannot be modified. However, because courts interpret the actual protection offered by a patent in light of the relevant prior art, the *de facto* protection offered by the focal patent shrinks. Consistent with this, Lee (2020) shows that these priority disclosures are associated with a decline in firm value.[8]

[6]For example, the infamous patent dispute between the University of California and Broad Institute regarding who first developed the CRISPR-Cas9 gene editing technologies is still being litigated (Cohen, 2018).

[7]A note by Moderna Inc. in a recent 10-Q report provides a good example: "Because certain U.S. patent applications are confidential until the patents issue... third parties may have filed patent applications for technology covered by our pending patent applications without our being aware of those applications, and our patent applications may not have priority over those applications. In addition, publications of discoveries in the scientific literature often lag behind the actual discoveries, and patent applications in the United States and other jurisdictions are typically not published until 18 months after filing, or in some cases not at all. Therefore, *we cannot be certain that we were the first to make the inventions claimed in our patents* or pending patent applications, or that we were the first to file for patent protection of such inventions, including mRNA-1273." (Moderna (2020), emphasis ours)

[8]Our method identifies changes to patent protection that occur *after* patent grant. Thus, this paper differs from previous work that focused on changes to patent scope that happen during the examination process (e.g., Kuhn and Thompson, 2019).

To account for possible unobserved differences in patents that experience such priority disclosures, we develop a control group of scientific papers, each paired to a patent. These papers belong to the same firm and experience similar disclosures, except that they do not suffer from a reduction in protection because the potentially protection-reducing patent has a later priority date, and thus is not prior art. Of course, the decision to study patent-paper pairs limits our investigation to firms and research areas where patents are effective. Not all research conducted within firms is protected by patents, so we are likely studying research the firm deemed important enough to patent. On the other hand, an advantage of our approach is that one can compare outcomes within the same firm. That is, one can estimate the impact on follow-on research at the scientific trajectory level within a firm, rather than across firms.

We use data on patents and papers related to U.S.-based public firms between 1990 and 2015 from Arora, Belenzon, and Sheer (2019), which yields two main findings. First, we find that firms move away from research trajectories where their related patent protection is weakened. On average, the appearance of protection-reducing prior art for a patent is related to a 19% reduction in scientific citations *from within the firm* to the paired scientific paper. Importantly, there is no effect for citations from outside the firm.

Second, firms in thinner technology markets are affected more by the loss of patent protection (i.e., invest less in research) whereas those in thicker markets can compensate more easily by transacting with other firms. This evidence favors substitution over complementarity. When we compare the response of small and large firms (measured by sales), we find qualitatively similar effects, although the differences are not statistically significant. This may reflect the weakness of firm size as a measure of commercialization capability, which is likely to be innovation-specific. Furthermore, if complementary capabilities are important, small firms are more likely to invest in research when they can capture rents even without having to commercialize themselves, i.e., in fields with thick and well-functioning markets for technology.

2 Analytical framework

Consider a firm that has made a scientific discovery and is deciding on investment in follow-on research. Follow-on research enhances the value of the initial discovery. Specifically, the value of discovery is vr, where r is the follow-on research and v indexes the quality of the discovery. The fraction of the value that the firm captures is represented by $\phi(X, m)$, $\frac{\partial \Phi}{\partial X} \geq 0$; $\frac{\partial \Phi}{\partial m} \geq 0$, where X represents protection from the patent on the initial discovery, and m represents the firm's commercialization capability. If there is a market for technology, the firm may also license the innovation to a buyer with superior commercialization capability.[9]

2.1 Baseline model

Let $\Pi(r; X, m, q)$ be the profit of the inventor, $\Pi = vr\Phi(X, m) - \frac{1}{2}cr^2$, where c is the cost of one unit of follow-on research. The optimal level of follow-on research, r, is given by $\dfrac{v\Phi(X, m)}{c}$. If the effective patent protection declines from X to $X - x$, follow-on research will fall:[10]

$$\frac{\partial r}{\partial x} = -\frac{v}{c}\frac{\partial \Phi(X, m)}{\partial X} \leq 0 \tag{1}$$

The fall in follow-on research is smaller for firms with greater commercialization capability if commercialization capability m and patent protection X are strategic substitutes (i.e., if $\frac{\partial^2 \Phi}{\partial X \partial m} < 0$) and greater otherwise. Formally,

$$\frac{\partial^2 r}{\partial x \partial m} = -\frac{v}{c}\frac{\partial^2 \Phi(X - x, m)}{\partial x \partial m}\bigg|_{x=0} \geq 0 \iff \frac{\partial^2 \Phi(X, m)}{\partial X \partial m} \leq 0 \tag{2}$$

Equation 2 formalizes the intuition that if patent protection is more valuable to smaller firms with weaker commercialization capability, then follow-on research by smaller firms will respond more to changes in patent protection. If commercialization capability is a strategic complement for patent protection, then the reverse will be true.

2.2 Commercialization with market for technology (MFT)

The firm commercializes internally if the value from internal commercialization exceeds the value any potential buyer can derive from the invention, net of transaction costs. That is, the invention will be licensed or sold to another firm if net gains from trade are positive. Denote by the subscript 0 the buyer representing the highest gains from trade. The value to the buyer is $vr\Phi(X, m_0)$, where m_0 is the buyer's commercialization capability. Let τ represent transaction costs, including the cost of transferring tacit know-how in the transfer and any costs due to imperfect contracting. We assume transaction costs are

[9] Galasso et al. (2013) argue that trade in patents invented by individuals may also be driven by differences in ability to enforce patents.

[10] In equation 1, we are evaluating the derivative of $\Phi(X - x, m)$ at $x = 0$, and shall do so throughout.

proportional to the value of the invention.[11] Ignoring potential rent-dissipation from product market competition, the gains from trade are simply $vr\{(1-\tau)\Phi(X,m_0) - \Phi(X,m)\}$. The inventor licenses if $(1-\tau)vr\Phi(X,m_0) \geq vr\Phi(X,m)$. Let $m^*(X,m)$ represent the minimum level of commercialization capability of the buyer such that gains from trade are non-negative. That is, $(1-\tau)\Phi(X,m^*) = \Phi(X,m)$

If the inventor appropriates $1 \geq \lambda \geq 0$ share of the gains from trade, its payoff from licensing is as follows:

$$\text{Expected payoff} = \Pi = \begin{cases} vr\Phi(X,m) + \lambda vr\{(1-\tau)\Phi(X,m_0) - \Phi(X,m)\} & \text{if } m_0 \geq m^* \\ vr\Phi(X,m) & \text{otherwise} \end{cases}$$

When the inventor decides on its follow-on investment, it is uncertain about licensing possibilities. Formally, we assume that m_0 is a random variable with distribution function $G(m_0)$. The expected profits are:

$$\begin{aligned} \Pi &= vr\Phi(X,m) + \lambda vr\int_{m^*}^{1}\{(1-\tau)\Phi(X,m_0) - \Phi(X,m)\}dG - \frac{cr^2}{2} \\ &= vrA - \frac{cr^2}{2}, \quad \text{where } A = \Phi(X,m) + \lambda\int_{m^*}^{1}\{(1-\tau)\Phi(X,m_0) - \Phi(X,m)\}dG \end{aligned} \tag{3}$$

The optimal follow-on investment is $r = \frac{vA}{c}$. Notice that expected profits are always higher when commercialization through a market for technology is possible. As a result, follow-on investment is always greater with a market for technology. Intuitively, the market is like an option, which is always beneficial. Indeed, the expression for A has two parts. The first corresponds to internal commercialization. The second represents the option value of commercializing through the market. The first increases with the firm's commercialization capability, whereas the second decreases with the firm's commercialization capability.[12] Equation 3 also implies that expected profits fall with transaction costs τ. In what follows, we focus on the limiting case of $\tau \to 0$, which also implies $m^* \to m$.

2.2.1 Reduction in patent protection

$$\begin{aligned} \frac{\partial r}{\partial x} &= \frac{v}{c}\frac{\partial A}{\partial x} = -\frac{v}{c}\left(\frac{\partial\Phi(X,m)}{\partial X} + \lambda\int_{m^*}^{1}\left\{(1-\tau)\frac{\partial\Phi(X,m_0)}{\partial X} - \frac{\partial\Phi(X,m)}{\partial X}\right\}dG\right) \\ \implies \left.\frac{\partial r}{\partial x}\right|_{\tau\to 0} &= -\frac{v}{c}\left(\frac{\partial\Phi(X,m)}{\partial X} + \lambda\int_{m}^{1}\left\{\frac{\partial\Phi(X,m_0)}{\partial X} - \frac{\partial\Phi(X,m)}{\partial X}\right\}dG\right) \end{aligned} \tag{4}$$

[11] It is plausible that these costs are higher when patent protection is narrower (e.g., Arora (1995, 1996), Lee (2020)) so that $\frac{\partial\tau}{\partial x} \leq 0$. This effect tends to amplify the response of follow-on research to patents.

[12] Firms with greater commercialization capability have a lower value of using the market for technology.

Comparing equation 4 to equation 1 shows one additional term. The second term corresponds to how a reduction in patent protection affects the gains from trade. This term is zero under independence, negative under complementarity and positive under substitutability. The potential buyer, with greater commercialization capability, has a lower marginal value for patent protection under substitutability. Therefore, markets for technology dampen the reduction in follow-on research under substitutability.

2.3 Transaction costs and patent protection

Arora (1995) argues that broader patents can support contracts for transfer of tacit knowledge. More efficient contracts reduce the loss in value suffered by transactions in the market for technology. Simply put, it is plausible that τ is reduced by broader patents. Lee (2020) shows, in a large sample setting, that a reduction in patent protection reduces the likelihood that the patent is licensed. Assuming $\frac{\partial \tau}{\partial X} \leq 0$, there is an extra positive term, as shown in equation 5 below. If transaction costs fall with patent protection, then follow-on research is more responsive to changes in patent protection under markets for technology, all else held constant.

$$\left.\frac{\partial r}{\partial x}\right|_{\tau \to 0} = \frac{v}{c}\left(\frac{\partial \Phi(x,m)}{\partial x} + \lambda \int_{m^*}^{1}\left(\frac{\partial \Phi(x,m_0)}{\partial x} - \frac{\partial \Phi(x,m)}{\partial x}\right) dG - \frac{\partial \tau}{\partial X}\lambda \int_{m^*}^{1}(\Phi(x,m_0) dG\right) \tag{5}$$

2.4 Discussion

The setup described here can be thought of as a reduced-form version of the model described in Galasso and Schankerman (2018), in which the invalidation of a patent sets off a rent-dissipating patent race on the follow-on invention and reduces the expected payoff of the patent holder. The reduction in incentive for follow-on investment is potentially counteracted by a strategic incentive to win the race by increasing follow-on investment. This strategic incentive is absent in our decision-theoretic model. Consequently, the incentive to invest is directly related to the value of patent protection.[13] The other important difference has to do with markets for technology. In our setup, an invention whose patent has been weakened may still be traded. In Galasso and Schankerman (2018), an invention without a patent is assumed to be in the public domain, and has zero trade value.

[13]Galasso and Schankerman (2018) also assume that larger inventors (as measured by the size of their patent portfolio) have more productive research, although the incremental benefits diminish. The productivity of research if the focal patent is invalidated is potentially non-monotonic in the size of the portfolio. Thus, if competition in the patent race is very intense, then patents and size are strategic substitutes.

The main predictions of the model are summarized as follows. A reduction in patent protection reduces follow-on research within the firm. Further, if patent protection and commercialization capability are strategic substitutes, greater commercialization capability will make the firm less responsive to changes in patent protection, while the opposite is true if the two are strategic complements. Markets for technology provide the inventor a valuable option and therefore increase follow-on research. If patent protection is more valuable to larger firms (i.e., strategic complementarity), markets for technology will amplify how follow-on research responds to changes in patent protection and dampen the response if there is strategic substitution. An important empirical implication is that if the reduction in follow-on research is smaller when the firm operates in an active market for technology, this is inconsistent with patent protection being a strategic complement to commercialization capability. Instead, this is consistent with strategic substitutability.

3 Methodology

Following Lee (2020), we assume the effective protection provided by a focal patent is reduced when a closely related patent with an earlier priority date is disclosed after the grant of the focal patent. We label this event as a "priority disclosure." We use textual similarity measures to assess similarity between patents. We identify patent-paper pairs using the textual overlap between the patent claims text and scientific paper abstracts. We create a matched control group by identifying patent-paper pairs that experience similar sequences of disclosure, save only that the related patent has a later priority date and is therefore not prior art for the focal patent. Lastly, we compare levels of internal patent and scientific citations received by the treated and control papers.

3.1 Patent-paper pairs

When firms publish a scientific discovery but also file for a patent on related inventions, it results in a *patent-paper pair* (Ducor, 2000). Murray (2002) introduced the method of observing citations to patent-paper pairs to analyze the commercialization of science. Murray and Stern (2007) used a similar approach to test whether patents hinder the overall levels of follow-on scientific research. Fehder et al. (2014) further examined how the effect of patents is moderated by the type of institutions. Thompson et al. (2018) used inventor names to match patents to scientific papers and examined the effect of patent licensing on follow-on scientific research by others.

We use automated textual methods for matching patents and scientific papers. We clean the text using stemming and stop words and revert abbreviations to their original content. We then use a "term frequency-inverse document frequency" (TF-IDF) to calculate weights for each word. One key challenge is that inventors tend to demonstrate patent novelty by expressing similar ideas using different words. To address this challenge, we calculate word-stem pair distances based on patent examiner rejection letters. When a patent is rejected due to lack of novelty or for obviousness, examiners cite the relevant prior art that is technically similar. Using these citations, we can identify different word stems that are likely to describe the same technical invention. We compute a similarity score between a patent and a paper abstract using cosine similarity between the word vectors, while taking into account the word-stem pair distances described above. We then use a cutoff score to identify highly similar patents and papers.

When a patent and a paper are similar and associated with the same firm, we consider them a patent-paper pair. To further improve the match, we limit the absolute gap to seven years between the patent and paper publication years. Note that we do not constrain our matches on author names or crosswalks between patent categories and scientific research topics. We argue that when a patent is providing protection to the contents of a scientific paper, derivative findings and applications by the firm are likely to benefit from some level of protection by the focal patent. Thus, the focal patent is assumed to provide protection to follow-on research that is related to the focal paper.

3.2 Identification strategy

When two related discoveries are patented, the earlier invention is considered as relevant prior art to the later invention.[14] Yet, since patent examination periods vary, there are frequent cases where a proximate prior-art patent is filed *earlier* than the focal patent, but is not disclosed to the public until *after* the focal patent is granted. Since it has not yet been disclosed at the time of the grant of the focal patent, the prior-art patent could not have been officially recognized as such. These cases are especially prevalent when patents are continuations of undisclosed foreign patent applications. In these cases, the gap between the priority date and the first public disclosure could be longer than the standard 18-month gap enacted by the American Inventors Protection Act (AIPA) since November 2000.

Once the prior-art patent is disclosed, the focal patent arguably experiences an ex-post reduction of the protection it provides (see also section 4). We label such patents as treated patents. The earliest

[14]Bikard and Marx (2019) document many cases of scientific multiples. Thompson and Kuhn (2020) document similar overlaps in patent applications.

disclosure date for any given patent is defined as the earliest disclosure date within a DOCDB[15] patent family. Thus, information disclosed by patents outside the U.S. is taken into account. A disclosure date might be either the grant date of the patent or a pre-grant disclosure of a patent application that has priority.

To identify proximate prior art, Lee (2020) uses a similarity measure between patents based on their textual content, employing the same methodology that was described above for identifying patent-paper pairs. When a similar prior-art patent that is not owned by the same firm as the focal patent is disclosed after the publication of the focal paper, we consider it as a priority disclosure event. We argue that once a patent-paper pair is hit by a priority disclosure, the IP protection that the focal patent provides to the related research trajectories is reduced.

3.3 Sample construction

A direct comparison of treated patents and untreated patents might pick up relevant heterogeneity across research trajectories. Patents in research areas with high levels of competitive investment might have a higher probability of receiving a priority disclosure compared to patents that are less central to current research agendas. In addition, the appearance of a textually similar patent held by a competitor might affect follow-on investment not only through changes in patent protection, but also through the perceived competitive landscape. Once it is disclosed that a competitor is working in a similar research area, a firm might respond by speeding up research in this area or by shifting to other research areas (e.g., Clarkson and Toh, 2010).

We therefore construct a control patent-paper pair belonging to the same firm as the treated patent-paper pair. Similar to the treatment group, patents in the control group experience the disclosure of a textually similar patent by a competitor. However, unlike the treatment group, the disclosed patent was filed *after* the focal patent and therefore does not hold priority over it. Consequently, the disclosure of the competing patent does not change the effective protection offered by the patent in the control pair. Because both the treated and the controls experience a post-grant disclosure of a competing patent, we are controlling for effects related to the competitive landscape while focusing the analysis on the the effects of changes in the levels of patent protection. Since both the treated and the control pairs are from the same firm, we are also minimizing the effects of differences in citation or publication practices across firms.

[15]European Patent Office worldwide bibliographic data

4 Validation of priority disclosure events

To support our argument that priority disclosures tend to reduce focal patent protection and could be used as exogenous shocks, we provide several validation tests. The evidence suggests that priority disclosures are associated with a reduction in patent scope and that these events are not anticipated by the firm, nor by investors. Taken together, we argue that these results back our use of priority disclosures as exogenous shocks to post-grant focal patent protection.

4.1 Effect of priority disclosures on patent scope

According to Kuhn and Thompson (2019), a good and widely available measure of patent scope is the word count of the first independent claim of the patent. Patents with shorter claims provide more general protection, presumably because there are fewer restrictions on the claim. The authors argue that this measure is superior to previously used measures in the literature, such as the number of claims, the number of future citations and the number of patent classes associated with the patent. Compared to these measures, the word-count measure is better aligned with the law and the practice. It is also the only measure that is highly predictive for the scope of a set of patents as assessed by experts.

Thompson and Kuhn (2020) use the word-count measure to test the effect of winning a patent race on a set of outcomes. The authors identify "patent twins," in which two competing patents are filed at nearly the same time (6 or 18 months apart, per the specifications in the paper). Among these twins, one patent ("the leader") has priority over the other ("the follower"). The twins are connected through a mention by a patent examiner in a novelty rejection issued to the follower as a result of the disclosure of the leader. Described in another way, the leader is disclosed *within* the examination process of the follower and causes a patent examiner to reject the follower's claims. The authors show that losing the race is associated with a larger increase in the length (number of words in the first claim) of the follower relative to the leader.

Priority disclosures are a generalization of the "patent-twins" approach by relaxing the requirement for an explicit mention by a patent examiner. Using textual similarity, we identify closely related patents that would likely result in a novelty rejection if examined. This enables us to explore the effect of *post-grant* disclosures that are not visible to examiners during the examination process and compare citation outcomes in the periods before and after the appearance of the shocks.

To validate our measure, we first test whether *pre-grant* priority disclosures are associated with a greater reduction in patent scope, measured by the number of words in the first independent patent claim (longer claims are associated with smaller scope). Using data on patents filed by U.S.-based firms between the years 2000 and 2015, we identify patents that experience *pre-grant* priority disclosures. These events occur when there exists another patent that is textually similar to the focal patent, is not assigned to the same firm, is filed before the focal patent, but is disclosed before the grant of the focal patent. The disclosure of the priority patent should potentially result in a reduction of the final scope of the focal patent by expanding the claim wording.

Due to the American Inventor's Protection Act, the original filing text and the final granted patent text are publicly available for a large portion of patents filed after November 2000. We count the number of words in the first patent claim, in both the original filing and the granted patent. Out of about 625,000 patents for which we have both measures, we identify about 98,000 treated patents (15%).[16] For each treated patent, we find another patent assigned to the same firm, within the same 4-digit IPC and published in the same year. Our final sample includes 33,058 patents, of which half are treated and the rest are controls. Our panel for analysis includes two observations for each patent: one observation for the number of words in the first claim of the original filing and another for the number of words in the first claim of the final granted patent.

Our econometric model for this validation test takes the form:

$$W_{it} = \beta_0 + \beta_1 \text{Final}_{it} + \beta_2 \text{Treat}_i + \beta_3 \text{Final}_{it} \times \text{Treat}_i + \epsilon_{it} \tag{6}$$

In this specification, the dependent variable, W_{it}, is a word count of the first patent claim, for the i^{th} patent at stage t (either initial filing or granted patent). $Final_{it}$ is an indicator variable that is equal to 1 for final granted patent text and 0 for initial filing. $Treat_i$ is an indicator variable for patents that received a *pre-grant* disclosure shock. ϵ_{it} is an i.i.d. error term. Standard errors are clustered at the firm level. We expect $\beta_3 > 0$, implying a reduction in the patent scope following a *pre-grant* disclosure shock.

Table 1 presents the estimation results. The patents in our sample have, on average, 134 words in the first claim of their initial filing, without a significant difference between treated and the controls. By the final grant, on average, 30 words are added to the first claim of the control patents, and 40 words are added to the treated patents. The difference is statistically significant. In general, the scope of protection a patent provides tends to shrink during the examination process. The results in table 1 show that the

[16] Thompson and Kuhn (2020) use explicit patent mentions by examiners and find that 10-11% of patents are part of a patent race.

appearance of a previously undisclosed patent, flagged as "similar" (prior art) by our algorithm, further reduces the focal patent scope. We infer that our textual similarity measure is a plausible proxy for what a patent examiner would have considered prior art. Therefore, though *post-grant* priority disclosures cannot change the focal patent text, we argue that they do reduce the *de-facto* protection provided by the focal patents.

Insert Table 1 here.

4.2 Priority disclosures are not anticipated

Our identification strategy assumes that priority disclosures are not anticipated. We use the Kogan et al. (2017) measure of private patent value to compare the value of the treated and control patents at grant date. We expect an insignificant difference in patent value between treated and control patents. Using our baseline sample (as described in section 5), we test for an observed difference in patent value between treated and control patents. Table 2 shows that there is no statistically significant difference between the private value of treated and control patents.

Insert Table 2 here.

4.3 Market reaction to priority disclosures

Arora, Belenzon, and Lee (2020a) conduct an event study to test the effect of priority disclosures on stock-market returns of the focal firm. Disclosure shocks, happening at some date *after* the grant of the focal patents, should reduce their private value. The event study tested whether the stock market can pick up this reduction in value. The authors use daily stock returns of 972 firms (holding 1,858 treated patents). Using a three-factor model on a 40-day window, they found that, following a priority disclosure event, firms experience an average cumulative abnormal return of -1%. The authors found that, on average, smaller firms got a stronger reaction compared with larger firms, of -1.5% and -0.75% respectively. Larin et al. (2020) provide an external replication of these results. Using data provided by the original authors, the technical report conducts an independent test and finds similar results. Based on an event window of 5 days prior to the event and 31 days afterward, the authors found a small cumulative under-performance (less than 1%). By limiting the sample to small firms, the effect intensifies and is estimated at about 4%.

Taken together, these validation tests support our claims that priority disclosures are generally unpredicted by either the focal firm or the market, that they are associated with a decrease in *de-facto* patent protection and that this decrease has economic implications for the affected firms.

5 Data

We use a dataset on U.S.-based corporate utility patents and scientific papers provided by Arora, Belenzon, and Sheer (2021).[17] We start our analysis in 1990, the first year for which we have reliable data on scientific paper abstracts. The initial dataset consists of approximately 1.34 million patents and 821,000 scientific papers associated with 4,323 firms. This yielded 3.2 million possible pairs relating to 1,372 firms, composed of approximately 213,000 unique papers, and 448,000 unique patents. After further cleaning, we are left with approximately 16,000 unique scientific papers whose matching patents experienced a priority disclosure and approximately 13,000 papers with a "fake" priority disclosure.[18] We allow multiple papers to match with the same patent, both in the treatment and the control group. We mark a patent-paper pair as treated when the focal patent experienced a priority disclosure two or three years after the scientific paper was published. When multiple treated patents are paired with the same scientific paper, we choose the earliest priority disclosure date as the treatment date for the paper.

The final step is to match the treated and control pairs based on the characteristics of the scientific papers. For each treated pair, we match a corresponding control pair *originating in the same firm.* The pairs share a common publication year (year of publication of the scientific papers) and a common research topic based on the Web of Science list of research subjects. We allow control pairs to be matched with replacement with multiple treated pairs. Following this match, we end up with 4,387 unique scientific papers that are paired with 3,003 unique treated patents. The control group has 1,362 unique scientific papers and 1,189 unique control patents.

[17] The authors relied on data obtained from several sources: (i) Compustat for U.S. company data; (ii) BvD Orbis for subsidiary data; (iii) SDC Platinum for acquisitions and alliances data; (iv) Clarivate Web of Science (WoS) for scientific papers metadata; (v) PATSTAT 2016b for patent metadata. This dataset extends the older NBER patent dataset and provides a comprehensive source for corporate patents and scientific papers between 1980 and 2015. The data account for dynamic reassignment and changes in ownership structure (e.g., company name changes, mergers and acquisitions, spin-offs and divestitures). A dynamic association between patents and scientific papers to firms is critical for measuring *internal* citations correctly.

[18] We follow Lee (2020) in setting the similarity measure threshold for identifying disclosure shocks. Our results are robust for a set of alternative threshold levels.

5.1 Variable description

5.1.1 Scientific citations

We use Web of Science citations data to identify scientific papers by the same firm that cite the focal paper over the sample years of 1990-2015. These citations are labelled *internal* citations. All other citations, either by other firms or by researchers at universities and government labs, are identified as *external* citations. For our regression analysis, we keep annual citation counts for eight years from the publication of the paper, provided that Compustat data exists for the given firm in that year. We aggregate observations for pre- and post-treatment, such that each patent-paper pair has two observations in the panel. For OLS models, we calculate the average annual citations for the pre- and post-treatment periods. For negative binomial models, we sum over these years to keep the dependent variable as a count variable.

5.1.2 Patent citations to scientific papers

To further explore the firm's response to priority disclosures, we construct a measure of follow-on inventive activity that is related to the focal scientific paper. This measure consists of citation counts from patents by the same firm to the focal scientific papers in our sample. These citations, which are referred to as non-patent literature (NPL) citations, are provided by Marx and Fuegi (2020b).

5.1.3 Commercialization capability and markets for technology

Following our analytical model, we explore how the value of patent protection varies by the availability of commercialization capability. Since the latter is largely unobserved and innovation-specific, we begin by exploring how the effect varies by the thickness of markets for technology. Our measure of market thickness is based on Arora, Belenzon, and Suh (2020b), who identify patent sales by purging the USPTO Patent Assignment Dataset (PAD) of patent reassignments due to mergers, name changes and record corrections. For each IPC-4 (International Patent Classification) in our data, we calculate the percentage of patents that were reassigned between 1990 and 2015. We then use this measure to split our sample into (a) patents in technological areas with "thick" markets for technology and (b) patents that are part of "thin" markets. Next, we provide additional evidence by using average annual sales as a proxy for the presence of commercialization capability. The annual sales for firms in our sample range from \$17M to \$233B, and the average annual sales of the median firm in the sample is \$2.1B.

5.2 Descriptive statistics

Arora et al. (2021) identify a total of 3,889 U.S.-based public firms active between the years 1990 and 2015. There are 2,611 firms with at least one associated scientific paper. Due to our extensive matching procedures, our final sample consists of pairs originating from 81 of these firms. Table 3 presents summary statistics at the firm level. Though firms in our sample are larger than the overall population of innovative firms, our sample includes a wide range of firms in terms of size and R&D inputs and outputs.

Insert Table 3 here.

Table 4 presents descriptive statistics over the sample period. Our baseline scientific citations sample consists of 17,388 observations, split between treatment and control groups before and after treatment. The distribution of papers among firms is highly skewed, with 2,842 papers associated with the biggest firm. The average firm has 71 papers matched with 52 patents. Comparing average citations between the treatment and control group reveals some differences. While internal paper citations are similar at an annual average of about 0.4 citations, treated patents tend to have slightly more annual internal citations than the controls, with 0.26 and 0.2 annual citations respectively. Similarly, treated papers have on average 3 external annual citations, while the controls have 3.74. Lastly, treated patents receive slightly less external citations compared to the control patents.

Insert Table 4 here.

6 Estimation results

6.1 Econometric specification

Our baseline econometric specification takes the form:

$$C_{it} = \beta_1 \text{Post}_{it} + \beta_2 \text{Treat}_i + \beta_2 \text{Post}_{it} \times \text{Treat}_i + \epsilon_{it} \tag{7}$$

The dependent variable, C_{it}, is an average of annual internal citations between scientific papers, where i designates a patent-paper pair and t designates the time period (either pre- or post-treatment). For the negative binomial specification, we sum the citations over the same time period. $Post_{it}$ is an indicator variable that is equal to 1 in the post-treatment period and 0 otherwise. $Treat_i$ is an indicator variable for patent-paper pairs that received a priority disclosure. ϵ_{it} is an *i.i.d.* error term. The pre-treatment period is either two or three years long and starts with the papers' publication year. The post-treatment period is the remaining years, up to eight years from publication, or the last year for which we have Compustat records for the given firm. Heteroscedasticity-robust standard errors are reported. According to our analytical model, we expect $\beta_3 < 0$, suggesting a reduction in the firm's research investments following a reduction in patent protection.

In addition, we estimate similar specifications in which the dependent variable is a count of annual internal non-patent literature citations (i.e., NPL, citations from a patent to a scientific paper). For both specifications, we also provide analyses where the dependent variables are counts of external citations, which are all citations originating outside the focal firm.

6.2 Baseline results: Patent protection and follow-on research

Table 5 presents the estimation results for the baseline specification. We observe a statistically significant difference between the treated and control observations following a reduction in patent protection. According to the point estimates in the OLS specification (Column 3), the average annual internal citations for the controls post-treatment is 0.321 (0.486-0.165). For the treated, the average is 0.26 (0.321-0.061), a reduction of 19%. This result persists in the negative binomial specification. In contrast, a reduction in patent protection does not seem to significantly affect the number of external citations (columns 1 and 2). This is consistent with Sampat and Williams (2019), who also find no effect of patent denial on follow-on research by others.

Columns 5-7 explore the heterogeneity of the effect by industry. The strongest effect is observed for life biomedicine research, followed by ICT & engineering. In life biomedicine, a reduction in patent protection is associated with a 35% reduction in average annual internal citations ($\frac{-0.307}{0.473}$). In ICT & engineering, there is a 21% reduction ($\frac{-0.072}{0.429-0.097}$). In the physical sciences, we do not observe a significant difference between treated and controls.

The estimation results confirm that a reduction in patent protection reduces follow-on investment in related scientific research trajectories by the focal firm. The heterogeneity of the results by industry are consistent with findings in the literature that patents are more effective at protecting inventions in the life sciences (e.g., Cohen et al. (2000)).

Insert Table 5 here.

6.3 Patent protection and follow-on invention

Patent citations are frequently used as a measure of follow-on invention. Given the nature of our sample, we estimate follow-on inventive activity by observing the effect of change in patent protection on patent to paper (NPL) citations.[19] Table 6 presents an analysis for patent to paper citations. The reduction in NPL citations indicates that, on average, following a reduction in patent protection, firms reduce their follow-on inventive activity related to the focal research trajectories. Specifically, the estimates in table 6 imply a 42% reduction in average internal NPL citations to treated papers ($\frac{-0.025}{0.046+0.022-0.016}$).

Insert Table 6 here.

A possible objection to our interpretation of the baseline results is that a reduction in citations might not be driven by reduced investments, but rather by a reduction in publishing. While we cannot refute this possibility completely, that we find a reduction in follow-on patents that cite the treated patent, as well as fewer follow-on patents that cite the paper paired with the treated patent, makes it more likely that the firm reallocates resources away from the research area that has lost some patent protection. In summary, the evidence presented in tables 5, 9 and 6 implies that firms decrease their investments in research trajectories that have been affected by a reduction in patent protection.

6.4 Markets for technology

Columns 1-3 in table 7 present subsets of the sample, split by our measure of market thickness. The dependent variable is average annual paper-to-paper citations. We compare firms operating in 4-digit IPCs where patents are less likely to be traded (Column 1, thin markets for technology) with firms operating in areas with a higher share of traded patents (column 2, thick markets for technology).[20] We observe that firms operating in a thinner market for technology are *more* responsive than firms operating in thicker markets. In thin markets, we estimate a 37% reduction in follow-on research compared to the controls ($\frac{-0.164}{0.442-0.059+0.054}$), while in thick markets the estimated reduction is statistically insignificant. This is consistent with patent protection being a strategic substitute for commercialization capability.

Insert Table 7 here.

[19] Section 7 provides estimates of the effect on patent-to-patent citations.

[20] On average, patents in thick markets are twice as likely to be reassigned (5.2% reassignment level), compared to patents in thin markets (2.5% reassignment level).

6.5 Commercialization capability

Commercialization capability is typically innovation-specific and cannot be directly observed in our data. We proxy for the presence of commercialization capability by observing firm size (measured as average annual sales). Recall that if commercialization capability and patents are strategic substitutes, then smaller firms should be more responsive to reductions in patent protection. On the other hand, if commercialization capability and patent protection are complements, then firm size should amplify the response.

Columns 4-6 in table 7 present an analysis of the changes in internal citations by firm size. Observing the interaction terms in columns 4 and 5, we find a stronger response in small firms. However, the difference between the two is not statistically significant (column 6). We conduct a complementary regression analysis of the interaction between treatment, paper age and firm size (see figure A1). The results suggest that by the third year after treatment there is a statistically significant difference between small and large firms in the level of the response.

Table 8 provides additional analysis of the effect by subsetting the sample into four groups based on firm size and market thickness. Both within small firms and large firms, we notice a significant difference in response between thin and thick markets. The positive coefficient estimate for large firms in thick markets does not fit with our predictions. Among the four groups, the strongest effect is observed in small firms operating in thin markets for technology.

Insert Table 8 here.

Our analysis of the effect by firm size and market thickness provides an indication that research trajectories in smaller firms, and firms operating in thin markets, are more affected by the level of patent protection. Our theoretical predictions state that markets for technology could dampen the responsiveness to changes in patent protection only if patents and commercialization capability are strategic substitutes. Therefore, taken together, our results on responsiveness by firm size and the market thickness suggest that patents and commercialization capability are strategic substitutes.

7 Robustness

The construction of the sample in the previous sections includes multiple filtering steps and matching procedures. First, patents are paired with publications within the same firm. Then pairs are tagged as either treatment or control, and lastly these pairs are matched to create a balanced sample. The downside to this process is that it results in a rather limited sample of patents and papers originating from only 81 firms (out of about three thousand public firms who publish scientific papers).

To provide additional evidence for the effect of patent protection on follow-on investments in innovation, we construct a second sample. Here, we match patents without requiring a pairing with a scientific paper. A central benefit of this sample is that we can match treated and control patents based on their characteristics. We then compare follow-on internal patent citations to the focal patents in the sample.

As in previous sections, we use data from Arora, Belenzon, and Sheer (2021). Since most disclosure shocks happen within the first year following patent grant, we filter on patents with a disclosure shock (or fake disclosure shock) within that year. This increases the sample size, at the cost of a short pre-treatment term.[21] We match a treated patent with a control patent originating in the same firm, granted in the same year and sharing a 4-digit IPC over the years 1980-2012. We allow matching with replacement. Our matched sample consists of 45,401 treated patents matched with 24,888 controls, originating from 766 distinct firms.

Table 9 presents the estimation results. We observe a statistically significant difference between the treated and control patents following a reduction in patent protection. On average, the treated receive 4% less citations post-treatment ($\frac{-0.017}{0.315+0.02-0.089}$). We also attempt to explore how our results vary by firm size and the thickness of the market for technology. The sample is split at the median firm size and market thickness. Results in columns 3 and 6 are not statistically significant, possibly due to small sample size. However, the magnitudes of the interaction coefficients in all columns are consistent with our previous results: small firms are more responsive to changes in patent protection. In contrast to our previous results, here there is no clear difference between firms in thin and thick markets.

Overall, these results provide some additional evidence, over a larger sample of U.S.-based public firms, for the importance of patent protection for follow-on investments in innovation.

8 Conclusions

In this paper, we tackled a question fundamental to the management of science and technology: does intellectual property protection spur firms to invest in scientific research, and under which conditions is this effect strongest? Answers to these questions matter for the strategic management of firms as well as

[21] Our results are qualitatively robust to several other filtering choices.

understanding the distribution of nearly half of U.S. investments in scientific research that is conducted outside of universities or government labs. Although past work has investigated the impact of patents on whether individual firms continue to *patent* (Farre-Mensa et al., 2019; Galasso & Schankerman, 2018), or whether scientific inquiry proceeds in the industry more generally (Murray & Stern, 2007; Sampat & Williams, 2019), no work, to our knowledge, has shown whether firms are motivated to invest in scientific research when they can claim temporary monopoly over their discoveries.

Although this relationship might seem self-evident, the literature has largely focused on indirect motives for firms to conduct research with their own money: developing absorptive capacity (Cockburn & Henderson, 1998; Cohen & Levinthal, 1989; Henderson & Cockburn, 1994), attracting scientists (Stern, 2004) and impressing investors, regulators and customers (Azoulay, 2002; Hicks, 1995). Our result suggests a direct relation between scientific findings and inventive activity and spotlights original formulations by Bush (1945) and Teece (1986), who viewed science as a direct input into innovation. The incentives that patents provide firms to conduct research also stand as a positive effect of the much-maligned patent system.

We also provide identifying evidence that patents and commercialization capabilities are substitutes rather than complements. Our finding that patents matter more in "thin" markets for technology, where the focal firm cannot easily import commercialization capabilities by trading with other firms, contradicts the notion that patent protection and commercialization capability are complements. This result also helps resolve conflicting results in the literature regarding the relationship between patents and commercialization capability (Cockburn & MacGarvie, 2011; Fischer & Henkel, 2013; Hall et al., 2013; Helfat, 1994; Leiponen & Byma, 2009), which have largely been produced by comparing firms by size—the identifying assumption being that smaller firms lack commercialization capabilities. We too find very limited differences by firm size, but this is because considering only the firm's internal capabilities ignores the potential to augment its own capabilities by transacting in "thick" technology markets. Only when considering the full range of commercialization capabilities available to the firm—including those of other firms—is this tension resolved.

Our results help to explain why the innovation ecosystem is characterized by a growing division of innovative labor with startups as sources of new ideas, as patent protection has strengthened since the mid-1980s. Our results imply that there are strategic substitutes for commercialization capability: Patent protection is more valuable for smaller firms lacking commercialization capability. Markets for technology further encourage even firms lacking commercialization capability to invest in research with the confidence that they can profit from it by licensing or selling their inventions to others. Stronger intellectual property rights help, especially if they facilitate such transactions. Thus, stronger patents encourage research but can also shift the locus of research.

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Table 1: Impact of Pre-grant Priority Disclosures on Length of Patent's First Claim

	Word Count	log(Word Count)	Word Count	
	All	All	Small Firms	Large Firms
Model:	(1)	(2)	(3)	(4)
Family	OLS	OLS	OLS	OLS
Post × Treated	9.97***	0.078***	7.03	11.6***
	(2.93)	(0.011)	(4.62)	(3.77)
Post	29.4***	0.278***	26.6***	31***
	(1.98)	(0.007)	(3.23)	(2.5)
Treated	2.66	-0.013*	3.55	2.16
	(2.29)	(0.008)	(3.6)	(2.95)
(Intercept)	134.7***	4.62***	145.4***	128.7***
	(1.51)	(0.006)	(2.46)	(1.92)
Observations	66,116	66,116	24,012	42,104
R^2	0.00883	0.0533	0.00752	0.00961

White-corrected standard-errors in parentheses

The table presents difference-in-differences analysis of the effect of pre-grant disclosure shocks and final patent scope. We use corporate patents that are filed after November 2000, for which we have the texts of the initial application and the final granted patent. Patent scope is proxied by counting the number of words in the first patent claim. For each patent, words are counted in the original patent application and again in the final publication of the granted patent. Treated is an indicator variable for patents that experienced a pre-grant priority disclosure shock. This shock is caused when a proximate prior-art invention is disclosed after the focal patent is filed, but before the examination process ends. Post is an indicator variable that distinguishes between the initial application and the final patent text. In columns 3 and 4 the sample is split based on the average firm sales.

Table 2: Private Value of Patents at Grant

	Patent Value			
	All	Life & Biomedicine	Physical Sciences	ICT & Engineering
Model:	(1)	(2)	(3)	(4)
Family	OLS	OLS	OLS	OLS
Treated	1.48	18.7	1.05	-0.658
	(1.87)	(13.4)	(1.32)	(0.860)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Observations	8,627	1,040	3,948	6,269
R^2	0.45782	0.32748	0.61348	0.20889

Standard-errors clustered by firm

The table presents an analysis of the difference between the estimated private value of patents at grant (Kogan et al., 2017) between treated and control patents in our sample. We add firm fixed-effects to control for possible endogeneity of some missing values. Columns 2-4 present subsamples by research area. Note that some observations are tagged with multiple areas.

Table 3: Firm Level Summary Statistics

Variable	Num. Obs.	Mean	SD	Distribution Min	p25	p50	p75	Max
All innovative firms								
Annual Patents	3889	14.96	86.58	0	0.5	1.55	5.42	3506.84
Annual Papers	3889	8.73	57.23	0	0	0.33	2.44	1805.57
Market Value ($mm)	3889	2249.96	13891.73	0.056	33.6	132.51	649.9	531425.99
Assets ($mm)	3889	1063.23	6364.05	0.001	8.58	41.4	267.56	210050.5
Sales ($mm)	3889	1416.34	7840.34	0	16.11	82.4	425.98	233668.31
R&D exp. ($mm)	3889	65.02	331.62	0	2.18	8.94	30.55	6969.4
Publishing firms								
Annual Patents	2611	21.46	105.02	0	0.83	2.53	8.84	3506.84
Annual Papers	2611	13.01	69.45	0.016	0.31	1.23	5.23	1805.57
Market Value ($mm)	2611	3135.44	16746.9	0.062	60.82	230.53	1066.2	531425.99
Assets ($mm)	2611	1493.89	7709.02	0.0035	11.72	64.59	462.6	210050.5
Sales ($mm)	2611	1993.77	9505.95	0	20.31	116.67	713.19	233668.31
R&D exp. ($mm)	2611	91.35	398.59	0	4.45	16.17	46.12	6969.4
Sample firms								
Annual Patents	81	330.81	468.88	5.2	61.23	201.45	416.79	3506.84
Annual Papers	81	244.99	303.55	1.16	55.35	141.56	311.41	1805.57
Market Value ($mm)	81	43083.07	73959.42	39.21	5263.7	16579.13	43013.81	531425.99
Assets ($mm)	81	16890.79	31642.71	9.47	1410.66	7134.27	17001.5	210050.5
Sales ($mm)	81	21278.69	38094.49	17.67	1972.47	6309.44	23937.98	233668.31
R&D exp. ($mm)	81	1392	1614.19	4.45	310.17	787.76	1666.58	6969.4

Notes: The table presents summary statistics for firms in our data. The first part presents statistics for all US-based public firms in the data between 1990 and 2015. The second part presents statistics conditional on publishing at least one scientific paper. The third part presents statistics for the firms in our final sample. Variables are first averaged across firm-years and then averaged between firms.

Table 4: Summary Statistics

Variable	Num. Obs.	Mean	SD	Distribution Min	p25	p50	p75	Max
Papers per firm	81	70.98	319.8	2	3	9	26	2842
Patents per firm	81	51.75	220.01	2	2	7	23	1948
Treatment Group								
Paper publication year	4387	2001.16	5.33	1990	1998	2002	2005	2010
Patent grant year	3003	2003.1	5.3	1989	1999	2003	2008	2012
Disclosure year	4387	2003.57	5.29	1992	2000	2004	2008	2012
Internal paper citations	4387	0.37	0.42	0	0.11	0.22	0.44	5.67
External paper citations	4387	3	8.69	0	0.44	1.33	3.22	336.78
Internal patent citations	3003	0.26	0.52	0	0	0.11	0.33	6.56
External patent citations	3003	1.8	2.88	0	0.38	1	2	38
Control Group								
Paper publication year	1362	1999.85	5.32	1990	1996	1999	2004	2010
Patent grant year	1189	2001.58	5.46	1989	1998	2001	2006	2012
Disclosure year	1362	2002.29	5.28	1992	1998	2002	2006	2012
Internal paper citations	1362	0.41	0.45	0	0.11	0.22	0.5	5
External paper citations	1362	3.74	6.57	0	0.67	1.67	4.11	117.38
Internal patent citations	1189	0.2	0.42	0	0	0	0.22	3.78
External patent citations	1189	1.97	3.2	0	0.44	1	2.22	52.67

Notes: The table presents summary statistics for the treatment and control observations used in the following analysis. Matching is done through publication year and subject pairing within the same firm. Citations are presented as an average across six years following publication. Internal citations are forward citations by the same firm. External citations are forward citations by authors outside the firm.

Table 5: Baseline Results: Paper-to-paper Citations

	External Citations		Internal Citations				
	All	All	All	All	Life & Biomedicine	Physical Sciences	ICT & Engineering
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Family	OLS	Neg. Bin.	OLS	Neg. Bin.	OLS	OLS	OLS
Post × Treated	-39.6	-0.087	-6.07	-0.157	-30.7	-0.609	-7.22
	(24.2)	(0.074)	(1.71)	(0.048)	(5.5)	(2.64)	(1.94)
Post	168.8	0.930	-16.5	-0.046	7.12	-35.7	-9.67
	(13.1)	(0.038)	(1.31)	(0.036)	(4.79)	(1.89)	(1.52)
Treated	-25.2	-0.107	1.51	0.030	3.21	0.635	1.15
	(8.5)	(0.037)	(1.19)	(0.024)	(2.7)	(2.08)	(1.29)
(Intercept)	247.7	2.14	48.6	0.502	47.3	62.8	42.9
	(6.06)	(0.025)	(0.858)	(0.018)	(1.85)	(1.5)	(0.934)
Overdispersion		0.534001		1.0118			
Observations	17,388	17,388	17,388	17,388	2,212	7,908	12,555
R^2	0.00968	–	0.03008	–	0.0243	0.08507	0.01609
Pseudo R^2	6e-04	0.01382	0.00279	0.00103	0.00219	0.00802	0.0015

White-corrected standard-errors in parentheses

The table presents difference-in-differences analysis of the relationship between the scope of patent protection and forward scientific citations. For each firm, we keep all observations with available Compuststat data between 1990 and 2015. Treated is an indicator variable for papers with paired patents which experienced a priority disclosure shock. This shock is caused when a proximate prior-art invention is disclosed after the focal patent is published. Post is an indicator variable for observations in the post-disclosure period. For each patent, observations are aggregated to the pre- and post- periods, up to 8 years from publication. For OLS models, the dependent variable is average annual citations by scientific papers to the focal paper, multiplied by 100 for clarity. For negative binomial models, the dependent variable is the summation of citations across the relevant years. Internal citations (columns 3-7) are citations where both the citing paper and the focal paper belong to the same firm. External citations (columns 1 and 2) are all other citations. In columns 5-7, research areas are defined by aggregating the Web of Science "subheading" field (note that some papers are tagged with multiple areas).

Table 6: Patent to Paper (Non-patent Literature) Citations

	External Citations		Internal Citations	
	All	All	All	All
Model:	(1)	(2)	(3)	(4)
Family	OLS	Neg. Bin.	OLS	Neg. Bin.
Post × Treated	-1.06	0.114	-2.52	-0.504
	(4.18)	(0.217)	(0.725)	(0.182)
Post	-5.98	0.066	-1.64	0.072
	(1.61)	(0.092)	(0.455)	(0.126)
Treated	6.36	0.259	2.24	0.384
	(2.46)	(0.100)	(0.601)	(0.105)
(Intercept)	19.9	4.21	4.6	2.74
	(1.33)	(0.066)	(0.350)	(0.076)
Overdispersion		0.027083		0.009272
Observations	17,420	17,420	17,420	17,420
R^2	0.00101	–	0.00474	–
Pseudo R^2	8e-05	0.00021	0.00052	0.00019

White-corrected standard-errors in parentheses

The table presents difference-in-differences analysis of the relationship between the scope of patent protection and forward patent citations to scientific papers. For each firm, we keep all observations with available Compuststat data between 1990 and 2015. Treated is an indicator variable for papers with paired patents that experienced a priority disclosure shock. This shock is caused when a proximate prior-art invention is disclosed after the focal patent is published. Post is an indicator variable for observations in the post-disclosure period. For each paper, observations are aggregated to the pre- and post-periods, up to 8 years from publication. For OLS models, the dependent variable is average annual citations by patents to the focal patent, multiplied by 100 for clarity. For negative binomial models, the dependent variable is the summation of citations across the relevant years. Internal citations (columns 3-4) are citations where both the citing patent and the focal patent belong to the same firm. External citations (columns 1 and 2) are all other citations.

Table 7: Responsiveness by Firm Size and MFT

	Internal Paper Citations Market for Technology			Internal Paper Citations Firm Size		
	Thin MFT	Thick MFT	All	Small	Large	All
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Family	OLS	OLS	OLS	OLS	OLS	OLS
Post × Treated × Thick MFT			20.4			
			(3.47)			
Post × Treated × Large						4.86
						(4.29)
Post × Treated	-16.4	4.02	-16.4	-10.2	-5.34	-10.2
	(2.46)	(2.45)	(2.46)	(3.85)	(1.89)	(3.85)
Post × Thick MFT			-21.1			
			(2.61)			
Treated × Thick MFT			-7.37			
			(2.41)			
Post × Large						-3.94
						(3.46)
Treated × Large						-1.84
						(2.7)
Large						5.45
						(1.93)
Thick MFT			8.71			
			(1.71)			
Treated	5.39	-1.98	5.39	3.07	1.23	3.07
	(1.57)	(1.82)	(1.57)	(2.35)	(1.34)	(2.34)
Post	-5.94	-27	-5.94	-13.2	-17.1	-13.2
	(2.04)	(1.63)	(2.04)	(3.15)	(1.44)	(3.15)
(Intercept)	44.2	53	44.2	44	49.5	44
	(1.18)	(1.24)	(1.18)	(1.67)	(0.968)	(1.67)
Observations	9,796	7,592	17,388	2,640	14,748	17,388
R^2	0.02149	0.05423	0.0345	0.03644	0.02945	0.03073
Pseudo R^2	0.00197	0.00515	0.00321	0.00348	0.00272	0.00286

White-corrected standard-errors in parentheses

The table presents an analysis of the baseline effects on paper to paper citations by firm size and thickness of the markets for technology. We proxy for size by measuring average sales and split the sample at the firm level using the mean. We keep the first 8 years of observations after publication of the paper or patent with available firm-level Compuststat data between 1990 and 2015. Thickness of the markets is proxied by a measure of the annual level of patent reassignment by IPC4. We define "thick" markets by splitting the sample at the mean. Columns 1-3 explore differences in market thickness, while columns 4-6 explore differences by firm size. Observations are at the pre- and post-treatment level for each paper. The dependent variable is average internal paper citations to the focal papers, multiplied by 100 for clarity. Treated is an indicator variable for pairs that experienced a priority disclosure shock. Post is an indicator variable for observations in the post-disclosure period.

Table 8: Responsiveness by Market Thickness in Small and Large Firms

	Internal Paper Citations Small Firms			Internal Paper Citations Large Firms		
	Thin MFT	Thick MFT	All	Thin MFT	Thick MFT	All
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Family	OLS	OLS	OLS	OLS	OLS	OLS
Post × Treated × Thick MFT			18.3			22.5
			(9.21)			(3.91)
Post × Treated	-23.7	-5.44	-23.7	-15.8	6.7	-15.8
	(8.09)	(4.42)	(8.08)	(2.58)	(2.94)	(2.58)
Post × Thick MFT			-15.8			-23.4
			(8.22)			(2.83)
Treated × Thick MFT			-9.87			-7.65
			(4.42)			(2.79)
Thick MFT			18.6			8.64
			(3.1)			(1.95)
Treated	10.9	1.03	10.9	4.89	-2.77	4.89
	(3.24)	(3)	(3.24)	(1.68)	(2.22)	(1.68)
Post	-1.63	-17.4	-1.63	-6.39	-29.8	-6.39
	(7.53)	(3.32)	(7.52)	(2.12)	(1.88)	(2.12)
(Intercept)	30.3	49	30.3	45.5	54.1	45.5
	(2.31)	(2.07)	(2.31)	(1.26)	(1.49)	(1.26)
Observations	766	1,874	2,640	9,030	5,718	14,748
R^2	0.033	0.04273	0.04794	0.02117	0.05879	0.0348
Pseudo R^2	0.00313	0.00411	0.00461	0.00194	0.00556	0.00323

White-corrected standard-errors in parentheses

The table presents an analysis of the baseline effects on paper to paper citations by firm size and thickness of the markets for technology. We proxy for size by measuring average sales and split the sample at the firm level using the mean. We keep the first 8 years of observations after publication of the paper or patent with available firm-level Compuststat data between 1990 and 2015. Thickness of the markets is proxied by a measure of the annual level of patent reassignment by IPC4. We define "thick" markets by splitting the sample at the mean. Columns 1-3 include small firms and columns 4-6 include large firms. Observations are at the pre- and post-treatment level for each paper. The dependent variable is average internal paper citations to the focal papers, multiplied by 100 for clarity. Treated is an indicator variable for pairs that experienced a priority disclosure shock. Post is an indicator variable for observations in the post-disclosure period.

Table 9: Matched Patent Sample: Internal Patent Citations

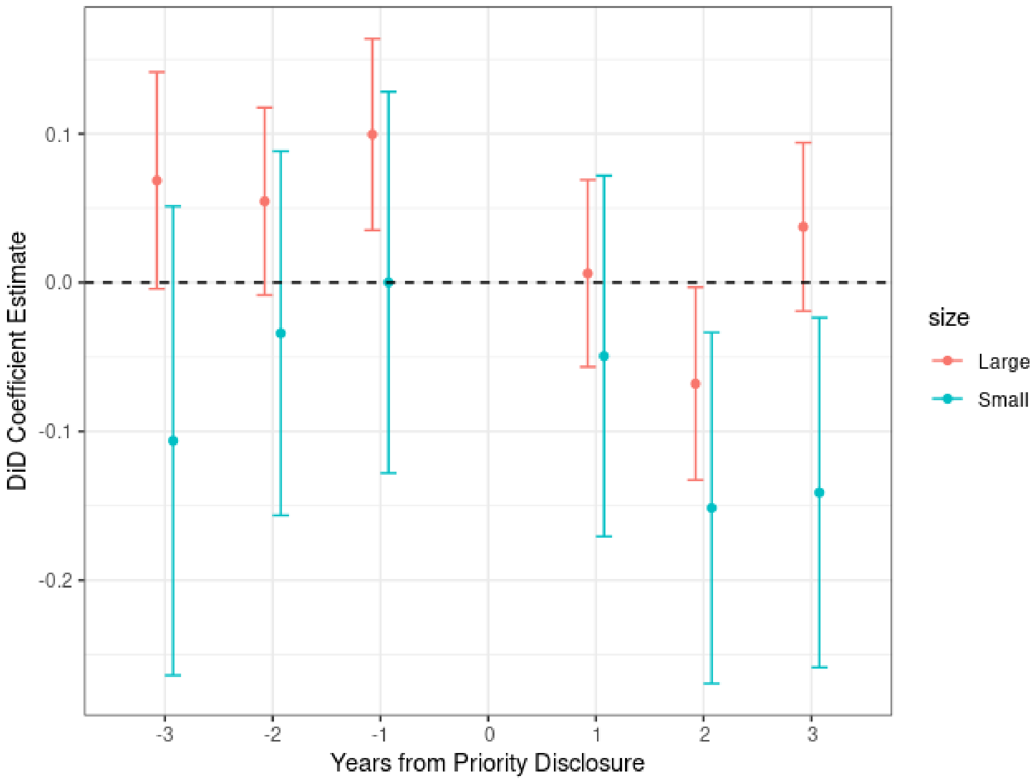
	All firms		Firm Size		Market for Technology	
			Small	Large	Thin	Thick
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Family	OLS	Neg. Bin.	OLS	OLS	OLS	OLS
Post × Treated	-1.74	-0.054	-3.41	-1.67	-1.76	-1.64
	(0.843)	(0.031)	(3.49)	(0.867)	(0.933)	(1.9)
Treated	1.96	0.060	2.68	1.93	1.88	2.42
	(0.667)	(0.021)	(2.67)	(0.687)	(0.732)	(1.61)
Post	-8.93	1.7	-5.99	-9.08	-9.11	-7.94
	(0.565)	(0.021)	(2.41)	(0.580)	(0.626)	(1.26)
(Intercept)	31.5	-1.15	26.3	31.8	32.3	27.3
	(0.461)	(0.015)	(1.81)	(0.476)	(0.509)	(1.07)
Overdispersion		0.207106				
Observations	180,306	180,306	8,040	172,266	153,288	27,018
R^2	0.00304	–	0.00253	0.00307	0.00303	0.00323
Pseudo R^2	0.00026	0.04028	0.00022	0.00026	0.00026	0.00028

White-corrected standard-errors in parentheses

The table presents difference-in-differences analysis of the relationship between patent protection and forward internal patent citations. For each firm, we keep all observations with available Compuststat data between 1980 and 2015. *Treated* is an indicator variable for patents which experienced a priority disclosure shock. This shock is caused when a proximate prior-art invention is disclosed after the focal patent is published. *Post* is an indicator variable for observations in the post-disclosure period. For each patent, observations are aggregated to the pre- and post periods, up to 8 years from grant. For OLS models, the dependent variable are average annual citations by patents to the focal patent, multiplied by 100 for clarity. For negative binomial models, the dependent variable is the summation of citations across the relevant years. Thickness of the markets is proxied by a measure of the annual level of patent reassignment by IPC4. We define "thick" markets by splitting the sample at the median. Columns 1 and 2 include all firms in our sample. Columns 3 and 4 compare small and large firms. Columns 5 and 6 compare patent by thickness of MFT. Observations are at the pre- and post-treatment level for each paper.

Appendices

Figure A1: Internal Paper Citations Analysis by Firm Size



The figure presents OLS coefficient estimates of the interaction between treatment and the distance (in years) from the priority disclosure years. Dependent variable is annual internal paper citations. Age and publication fixed effects are included. Standard errors are clustered by publication.