NBER WORKING PAPER SERIES

FIRST-MOVER ADVANTAGE AND THE PRIVATE VALUE OF PUBLIC SCIENCE

Ashish Arora
Sharon Belenzon
Bernardo Dionisi

Working Paper 28533
http://www.nber.org/papers/w28533

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2021

We thank Wesley Cohen and Jonathon Cummings, and seminar participants at Duke, Bocconi, and the University of Michigan for helpful comments. All remaining errors are ours. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

First-mover Advantage and the Private Value of Public Science
Ashish Arora, Sharon Belenzon, and Bernardo Dionisi
NBER Working Paper No. 28533
March 2021
JEL No. O3,O31,O34,O36

ABSTRACT

Technical progress increasingly relies on the use of scientific knowledge. But if much of this knowledge is in the public domain, can it be a source of private value? We find that average private returns to using public science are small, especially in crowded technical fields, consistent with the view that the expected profit from an input that others can easily access is low. However, private value is higher when a firm is the first to use science, partly because it can secure broader patents relative to later users. Finally, corporate participation in scientific research is a strong predictor of first use, especially of relevant science. This is consistent with the view that participation in science raises familiarity with relevant scientific advances.

Ashish Arora
Fuqua School of Business
Duke University
Box 90120
Durham, NC 27708-0120
and NBER
ashish.arora@duke.edu

Sharon Belenzon
Fuqua School of Business
Duke University
100 Fuqua Drive
Durham, NC 27708
and NBER
sharon.belenzon@duke.edu

Bernardo Dionisi
Fuqua School of Business
Duke University
100 Fuqua Drive
Durham, NC 27708
bernardo.dionisi@duke.edu

"... knowledge is regarded by economists as being "on the shelf" and costlessly available to all comers once it has been produced. But ... it frequently requires a substantial research capability to understand, interpret and to appraise knowledge that has been placed upon the shelf ... . The cost of maintaining this capability is high, because it is likely to require a cadre of in-house scientists who can do these things. And, in order to maintain such a cadre, the firm must be willing to let them perform basic research. The most effective way to remain effectively plugged in to the scientific network is to be a participant in the research process. ...basic research may be thought of as a ticket of admission to an information network" (Rosenberg, 1990: 170).

1 Introduction

Technical progress and scientific advance are closely interlinked (Mansfield, 1995; Cohen et al., 2002). In many, if not most, sectors of the economy, new technologies are increasingly scientific in nature (Narin et al., 1997; Fleming et al., 2019). The percentage of utility patents that cite science has increased from approximately 6% in 1980 to 30 % in 2015, and the average number of citations to science per patent has increased from 0.1 to 4.4 over the same period. Much of this scientific knowledge is published and available for all to use. Moreover, not all scientific discoveries are relevant for invention. A challenge for firms, therefore, is how to create value from an input that is of uncertain value and freely available to all.

We argue that first-movers may enjoy a significant advantage (Lieberman and Montgomery, 1998), but for that the firm has to participate in science to have the capacity to evaluate which scientific advances are relevant. The growing quantity of published research (Jinha, 2010) suggests that knowing where to look and what to use may be crucial. Recent evidence suggests that firms focus their attention on academic publications from locations with a high concentration of relevant patenting activity (Bikard and Marx, 2020). This may reflect longer term links with universities or even individual researchers. Bikard and Marx (2020) provide an insightful example on how Amgen secured crucial intellectual property building on the breakthrough purification of erythropoietin (EPO) by Professor Goldwasser at the University of Chicago. In a paper published in 1977, Goldwasser showed that EPO was responsible to stimulating production of red blood cells. Using the purified samples of EPO provided by

Professor Goldwasser, Amgen scientists could learn about the structure of EPO and identify the relevant genes. This knowledge enabled Amgen to produce EPO using recombinant DNA techniques, ahead of its rivals, and obtain the vital patent rights that underpinned Amgen's subsequent commercial success.

This example shows both the means by which a firm can be the first to use public science as well as the benefits of being a first mover in the use of public science. Simply put, firms' engagement in basic research is a source of a "first mover advantages," because participation in basic research increases a firm's ability to recognize and apply relevant extramural findings before others (Cohen and Levinthal, 1989; Rosenberg, 1990).

In this paper, we investigate the returns to the use of science, and how those returns differ between early and late users, as well as how the relative returns are conditioned by the number of potential users. The greater the number of potential users, the greater the relative rewards to being an early user, consistent with competition eroding the returns from the use a common resource. Second, we explore a specific mechanism for potential first mover advantage, namely the scope of patent protection obtained by the first movers. Finally, we explore whether and how being a first-mover is related to participation in scientific research by the firm.

We present three main findings. First, private returns to using science in invention are low. The difference in the private value of patents that cite science relative to patents that do not cite science is about 3%, despite the substantially higher technical quality of patents citing science, as measured by forward citations. In other words, the use of science appears to create social value, but only modest private economic returns. Consistent with the idea that private returns to using science are low because rival firms also have access to it, we find that the value of using science is lower in more competitive technology niches, defined as number of firms patenting in the same technology class as the focal firm. However, we also find that the negative relationship between value and competition can be substantially mitigated if the focal patent is the first to use the cited publication. Being a first mover in using science is associated with a reduction in the estimated negative effect of competition by half.

Second, exploring the source of first-mover advantage in the use of science, we find that first-movers obtain broader patents compared to subsequent users of the same scientific discovery, and more so when considering scientific findings that turn out to be useful for invention.

Third, active engagement in research, as measured by the number of publications authored by firms' employees, is positively associated with the first use of scientific publication, especially the first use of relevant publications. Exploring the mechanisms behind this relationship, we find that a firm is more likely to be the first to cite a scientific paper in its patent if the firm is familiar with the journal or conferences where the scientific discovery was disclosed. This is consistent with the view that corporate science is a ticket of admission into scientific communities.

We make two contributions. We theorize that firms can turn a publicly available input into a privately valuable resource by moving first, thereby pre-empting rivals. We document that firms can derive private value from the use of public science, particularly if they are the first to do so, and this first-mover advantage is more salient in more crowded niches. Further, we provide evidence for the widely theorised, but under-documented idea that firms which produce public research are also more likely to be among its *early* users. Thus, firms that invest in internal research are not just more likely to use science, but are also better able to extract private benefits from using public science.

On the methodological front, we leverage newly developed data (Kogan et al., 2017) on the value of patents to measure the private economic return to the specific invention, and distinct from the technical quality of the patent. In so doing, we respond to the call by Lieberman and Montgomery (2013) for forward-looking, rather than retrospective, measures of the benefits of being a first-mover, and for measures of economic return, rather than market-share or survival (Lieberman and Montgomery, 1988). However, our study does not extend to entry into the product market but is limited to the pre-entry stage of invention.

We next discuss our findings and contribution in the context of the different literatures that we draw upon and to which we contribute.

2 Prior literature and theoretical considerations

2.1 Reliance on science and patent value

A recent literature has studied the relationship between the use of science and patent value. Fleming and Sorenson (2004) find that patents citing scientific prior art receive more follow-on citations. Our paper confirms that finding but also shows that the mean private value of using science is low. That is, while inventions relying on science may be of higher technical quality and may generate greater social value, extracting private value from these higher quality patents is difficult. Poege et al. (2019) show a positive relationship between the quality of the articles cited by a patent and the technical quality of the patent. Our results are consistent. Patents citing articles published in high impact factor journals have higher private economic value relative to all other patents.

Watzinger and Schnitzer (2019) provide evidence that patents closer to scientific publications tend to have higher economic value than patents farther from science.[1] As in Watzinger and Schnitzer (2019) we use the monetary value of a patent developed by Kogan et al. (2017) to estimate the relationship between the use of science and the patent economic value. However, we compare patents that are the first to cite a paper with patents that only cite papers that have been previously cited by other patents, as well as with patents that do not cite scientific papers, whereas Watzinger and Schnitzer (2019) compare the average value of patents that directly cite science to patents that do so indirectly. Importantly, we take a within firm perspective, controlling for unobserved firm-specific factors that may be related to patent value, as well as to the distance between patents and science. This enables us to characterize the relationship between the use of science and value, and link this relationship to competition,

[1] They define closeness to science following Ahmadpoor and Jones (2017), so that, for instance, a patent has a distance of 1 from a publication if it cites the publication. It has a distance of 2 from a scientific publication if the patent cites a patent that in turn cites a scientific paper.

first mover advantage, and absorptive capacity.

2.2 First mover advantage

An influential literature has studied the conditions under which first movers have an advantage, the possible means by which first movers gain an advantage, and why some firms are more likely to move first (e.g., Lieberman and Montgomery (1988, 1998); Fosfuri et al. (2013)). Whereas the first-mover literature has focused on product markets, we focus on first movers in using a scientific discovery. This has some natural implications for how first movers gain an advantage. (Lieberman and Montgomery, 1988) identify three mechanisms whereby first-movers gain advantage: technology leadership, locking-in buyers, and preemption of key inputs, or winning a patent race (Fosfuri et al., 2013). In our context, the first mover, by being the first to patent, may gain a degree of market exclusivity, and in particular, may obtain broader patents. Needless to say, these different sources of advantage are not mutually exclusive. A patent may itself provide the patenting firm with the time to develop the complementary asset, while rivals are trying to invent around.

Lieberman and Montgomery (1998) argue that economic returns are the appropriate measure of first mover advantage rather than market share or survival, the focus of much of the literature. They argue that "First-mover advantages exist when the pioneering firm earns positive present value of profits as the consequence of its early entry (i.e. positive profits net of those attributable to more general types of firm proficiency). A serious problem confronting those engaged in empirical work is the fact that disaggregate profit data are seldom obtainable." An advantage of our study is the ability to observe a proxy for the monetary value a firm expects by pioneering the use of scientific findings. We have a measure of stock market returns associated with the patent (Kogan et al., 2017). In addition to being a measure of anticipated future economic return, albeit with some caveats, it is also specific to the invention rather than simply a firm level measure.[2] In other words, though limited to inventions that

[2] Indeed, Lieberman and Montgomery (2013) suggest stock-market capitalization as the appropriate measure.

are patented, this is a much finer grained measure of first mover advantage in the use of science, which allows us to control for unobserved firm specific effects. Thus, one can ask how economic returns from early versus late use of science differs within the same firm.[3]

Extensive as the literature is, pinpointing the specific ways in which early entry proves advantageous has remained a challenge in large sample settings. Our measure also allows us to explore how the economic returns are realized. We find that science-based patents are of higher technical quality, as reflected by citations received.[4] Importantly, patents that are the *first* to use a scientific discovery tend also to be broader in scope, compared to patents that are later users. That is, first movers are able to gain broader patent protection.

The literature has stressed the returns are contingent on a variety of factors (Lieberman and Montgomery, 2013). One such factor is the response of competitors. For instance, Agarwal and Gort (1996) document that competitor entry intro product markets has accelerated over time, reducing the lead time enjoyed by early entrants. However, the heightened competition would also imply lower profits for the later entrants. Thus the open question is how competition conditions the relative returns to early entry. We argue, with the help of simple analytical model, that find that the presence of potential users reduces the average returns from using science but enhances the relative returns of early users. Our empirical results are consistent with this reasoning.[5]

Although we draw upon the literature on first-mover advantage, there are important differences in context and measures. We use a forward looking measure of economic return, rather than market share or survival, and the measure is tied to the invention itself, rather than aggregate profitability of the firm as a whole. On the other hand, we do not observe entry into a market, only the timing of the use of science in invention. Further, we are confined to

[3]We are aware of only one similar prior study. Poletti et al. (2008) also use stock-market event study approach with product market announcements.

[4]Watzinger and Schnitzer (2019) show that these patents also tend to use more novel keywords.

[5]Another strand of the literature has examined the capabilities and resources that allow firms to move first. Starting with Mitchell (1989), the literature has examined a variety of such capabilities including marketing capabilities (Mitchell, 1991) and specialized assets (Tripsas, 1997), technical capabilities (Klepper, 2002) and manufacturing (Arora and Ceccagnoli, 2006). We complement this literature by pointing to absorptive capacity as a source of first-mover advantage.

publicly traded firms.

2.3 Investment in research and absorptive capacity

The vast literature on absorptive capacity (Cohen and Levinthal, 1989; Rosenberg, 1990) emphasizes the importance of corporate participation in research for accessing outside knowledge (Sauermann, 2010; Fabrizio, 2009). While this literature does not typically discuss first-mover advantage directly, it suggests that the firms that invest in basic research are better able to benefits from scientific discoveries that are ostensibly available to all. In our context, Baruffaldi and Poege (2020) show that firms that participate in a conference are more likely to cite a paper presented in that conference compared to papers at comparable conferences. We complement their findings by showing that firms are more likely to be early users when they participate in conferences and use scientific findings presented at the conference the firm attended. Our findings also resonate with the literature that has stressed the importance of pre-entry capabilities for entry (Helfat and Lieberman, 2002), and specifically for direction of innovation (Helfat, 1994).

In subsection 2.4 we explicitly model competition. Once a firm has used a scientific discovery in its inventions, and disclosed it by citing it in its patents, both the discovery and its relevance becomes clearer to others, including firms that may lack absorptive capacity. By so doing we stress that even firms without absorptive capacity may use scientific discoveries, but are unlikely to be first-movers because absorptive capacity is required to judge whether the scientific discovery is commercially valuable or not. The first-mover has more time to build or acquire the required inputs for commercialization. However, it can also use the patent itself to carve out a broader exclusive zone, thereby appropriating a larger share of the rents from its invention.

Empirically, we advance the literature on absorptive capacity by documenting not only that absorptive capacity is related to use, but also the economic return from the use, and how technical competition conditions the economic returns. In so doing, we connect the absorptive capacity literature to the strategic competition literature. This is timely in view of the growing division of innovative labor (Arora et al., 2018), whereby universities specialize in upstream research, and corporations specialize in downstream development and an increasing reliance on science of technology (Fleming et al., 2019; Marx and Fuegi, 2019). This division means that the using public science is becoming more important over time, but also that the challenge in profiting from it rises as firms' scientific capabilities deteriorate.

2.4 Analytical framework

To guide our empirical specifications, we develop a model in which scientific discoveries are publicly disseminated but their significance is initially only understood by firms that have absorptive capacity. In this model, absorptive capacity enables the firm to understand whether the discovery will or will not be useful for invention. If useful, the firm can move first to apply the discovery, thereby garnering a bigger piece of the intellectual space opened up by the discovery. Other firms can learn from the first-mover's experience and follow on. However, they have to work-around the invention claimed by the first-mover. Followers avoid having to invest in absorptive capacity but face a higher cost of working around the first-mover's patent.

The case of development of statins from Gambardella (1992) illustrates this idea. After scientific advance had demonstrated that high cholesterol levels were related to heart disease, firms such as Bristol-Myers, developed compounds such as Colestyramine, which removed bile acids from the body, thereby reducing some cholesterol. However, this was far less effective than reducing the production of cholesterol itself. In the 1970s Brown and Goldstein at the University of Texas elucidated how the body synthesizes cholesterol. Thereafter the search began for molecules that would block one of the 30 steps in the synthesis of cholesterol (Endo, 2010). However, it was Merck that successfully isolated lovastatin, the first compound that was effective in humans. Merck was first, in part because Merck scientists were familiar with Mevalonic acid, a key intermediate in the cholesterol pathway (Gambardella, 1992). Following the successful commercial debut of lovastatin (Mevacor) in 1987, other companies were able to enter. Parke-Davis (eventually acquired by Pfizer) was able to chemically synthesize a more potent statin, atorvastatin (Lipitor), by relying on molecular modeling of lovastatin. This example illustrates that internal scientific capability is useful for early users of science. However, once the applicability of a scientific discovery is demonstrated, followers need much lower levels of internal capability to apply the science, perhaps bringing to bear other capabilities (Gambardella, 1995).[6]

To fix ideas, consider the case where there are N firms that are active in an existing technological trajectory. The expected payoff from an invention in the existing trajectory is $\Pi^o(N)$, where the subscript o is a menomonic for "old". We assume that this payoff decreases with the number of active inventors N. Consider a scientific advance that potentially opens up a new trajectory. However, success is uncertain; there is a probability p that the leveraging the science will be successful, and with probability $1 - p$ it will be unsuccessful. The uncertainty will be resolved after someone actually tries to use the science in an invention. However for a firm with absorptive capacity, the uncertainty is smaller, because it gets a "signal" which is correlated with the true state. That is, absorptive capacity enables the firm to make a more informed decision. In the simplest, albeit less realistic, case, the signal is perfect - the firm knows with certainty whether the discovery is useful or not.[7]

Suppose that there is a single firm with absorptive capacity, which will pursue the discovery if the signal is positive and not pursue it if the signal is negative. To avoid unnecessary detail, we assume that p is always low enough such that firms without absorptive capacity will not pursue discoveries till the discovery has been shown to be useful i.e., till someone has successfully used it.[8]

[6]For instance, the synthesis of atorvastatin required expertise in chiral chemical synthesis at large scale, whereas lovastatin was a naturally product extracted from a fungus Roth (2002).

[7]The appendix shows that the assumption of a perfect signal can be relaxed with no essential changes in the results.

[8]In the appendix we discuss the decision to invest in absorptive capacity. The discussion here makes it clear that firms will under-invest in absorptive capacity because some of the benefits of such investment spillover to others. Investment in absorptive capacity enables a firm to assess the relevance of a scientific discovery. However, when it acts on it and successfully uses a scientific discovery, this also signals to other firms that the discovery is useful. The latter can gain some value but do not have to incur the cost of investing in absorptive capacity. The problem is exacerbated If the returns of the first-user fall as more firms use the discovery.

The final part of the story has to do with the inventive step or breadth of the invention, which is reflected in the intellectual space the inventor claims. We assume that the cost of invention is $c\frac{q^2}{2}$, and the expected gross return is pqv, where q represents the size of the inventive step (which implies a corresponding scope for the patent), and v is the unit value from an inventive step of size q in the new trajectory. Thus the payoff to pioneering the new trajectory, Π_1, where the subscript 1 denotes the first firm to enter the new trajectory, is $\Pi_1 = \max_{q_1}\{q_1 v - \frac{cq_1^2}{2}\} = \frac{(v)^2}{2c}$

We focus on the case where $\Pi_1 > \Pi^o(N)$. If the leader is successful, others will follow. The followers benefit from a resolution of the uncertainty. However, followers have a disadvantage in that the pioneer may lay claim to an intellectual space, forcing the follower to invent-around the pioneer's patent. Later followers would find progressively more intellectual space blocked off by those who had preceded them. We model this as an increasing cost of invention. That is, the second firm to use the discovery with an inventive step q_2 has an invention cost of $c\frac{q_2^2}{2}\beta(q_1)$, where q_1 is the inventive step of the pioneer, and $\beta(0) = 1, \beta' > 0$. More generally, for the r^{th} firm entering the new trajectory, the invention cost function is $c\frac{q_r^2}{2}\beta(Q_r)$ where $Q_r = \sum_{i=1}^{r-1} q_i$. However, because followers only enter if the scientific discovery is useful, they do not face any possibility of failure. Thus their gross return is $q_r v$. The payoff of the r^{th} firm is $\Pi_r = \max_{q_r}\{q_r v - \frac{cq_r^2}{2}\beta(Q_r)\} = \frac{v^2}{2c\beta(Q_r)}$. The optimal inventive step for the r^{th} firm entering a trajectory is $\frac{v}{c\beta(Q_r)}$. In other words, earlier users have better inventions and broader patents than later users.

We assume that firms have to choose i.e., they may either explore the new trajectory or stay in the old one.[9] Firms will enter till their payoffs equal those in the existing trajectory. That is, if n firms explore the trajectory, then ignoring integer constraints, a free entry equilibrium implies $\Pi_n = \Pi^0(N-n)$. Formally, the number of firms that use the discovery, n is characterized by $\frac{v^2}{2c\beta(Q_n)} = \Pi^0(N-n)$.

Note that a higher N implies a higher n. This is because an increase in N implies that

[9]Relaxing this assumption would imply that the returns from the new trajectory are zero for the marginal entrant, but the main result would be unaffected.

$\Pi^0(N-n)$ falls. To maintain the equality, Q_n must increase, and hence, n must be higher. A direct implication of the foregoing is that a higher N implies lower marginal returns in the new trajectory, and hence also lower average returns. It also implies that the returns of the first-mover relative to average returns would increase with N. This leads to the main result.[10]

Result: *The average return to the use of science is lower when there are more active inventors. However, the return to the first user relative to the average return to the use of science is higher when there are a more active inventors.*

In the empirical analysis, we also investigate the key assumptions of our framework. Specifically we test whether (i) firms with absorptive capacity are more likely to be first-movers, (ii) particularly for using relevant science. We further test that (iii) first-movers are more likely to get broader patents, (iv) especially for using relevant science.

3 Data

To explore the relationship between science and invention value we combine data from several sources: (i) USD denominated patent value from Kogan et al. (2017). We restrict the sample obtained from Kogan et al. (2017) to patents assigned between 1980 to 2010: 1,297,995 patents, assigned to 6,514 unique PERMCOs. To use the data from Arora et al. (2017), we consider only U.S.headquartered firms, which allows us to link companies' scientific publication activity and the use of science. Our estimation sample comprises 860,107 unique patents issued by the U.S. Patent and Trademark Office (USPTO) from 1980 to 2010 to 4,426 publicly traded, U.S. headquartered companies., (ii) patent citations to scientific publications from Marx and Fuegi (2019) – *PCS Data*, (iii) corporate publications from Arora et al. (2017), (iv) financial

[10] If competition directly affects payoffs from the use of science, the returns being a first mover should be higher. However, this complicates the formal analysis because first-mover has an incentive to deter entry by trying for a broader patent. Intuitively, allowing for preemption would strengthen the returns to being a first-mover. Further, greater competition in the existing trajectory would provide a greater incentive to the first-mover to preempt followers.

information from CRSP/Compustat, (v) front-page patent information from PatStat, and (vi) scientific articles from Microsoft Academic (Sinha et al., 2015). Below we describe how these data are used to construct the main measures used in this paper, summarized in Table 1.

3.1 Measures

Patent value. Patent values (ξ_i) are sourced from (Kogan et al., 2017). These are estimated using abnormal stock market returns of the company at the time the patent is granted. The patent value in millions of USD is deflated to 1982 prices using the Consumer Price Index. Kogan et al. (2017) estimate the economic value of a patent as a function of the idiosyncratic firm return, the *ex ante* probability of a patent being granted and a firm market capitalization before the issuing of the patent. This measure of the private economic value of patent allows researchers to distinguish it from its technical value, typically measured with forward citations.

The measure developed by Kogan et al. (2017), however, suffers from some drawbacks. As with all event study based measures, it assumes that the only reason for the abnormal return accruing to the firm's stockholders is related to the event under consideration, in this instance, the grant of a patent. There is also an important question about the time window used to measure the abnormal return. The shorter the window, the more tightly the focal event is linked to the stock price movement on the day but the less likely that the market price incorporates the relevant information. In the present context, a related drawback is that patents assigned to the same firm the same day (the USPTO issues patents once a week, on Tuesdays) are assigned the same average value. Notice however that what matters for our results is not the absolute values but whether the relative patent values are meaningfully measured. This is because we study the private economic value of patents that are the first to cite a scientific publication *relative* to those that only cite publications previously cited by other patents, and to patents that do not cite science.

The average patent value in our sample, is \$17.55 million in (1982 prices), while the median patent is valued at \$7.98 million. Values vary across industries, ranging from higher values in categories such as "Drugs & Med" where the average patent value is \$29 million, "ICT" with an average of \$18.9 million, to "Mechanical" with an average value of \$13 million.[11]

Use of science To measure the use of science in invention, we follow the growing literature employing non-patent literature (NPL) citations linked to scientific publications. We rely on Marx and Fuegi (2019), which provides an open source data-set, *PCS Data*, linking NPL citations of US patents, granted between 1926 and 2018, to scientific papers in Microsoft Academics. The *PCS Data* is a patent - NPL citation level dataset which assigns to each patent an NPL citation string matched, with various degrees of confidence, to a scientific publication in Microsoft Academics.[12] This match allows researchers to classify whether an NPL citation contains a link to a scientific paper.

While patent citations, specifically patent-citations-to-patents, have been criticized as a measure of knowledge flows (Jaffe and Trajtenberg, 2002; Roach and Cohen, 2013), recent evidence suggests that patent citations to scientific papers suffer less from the drawbacks afflicting patent citations to patent. Specifically, patent citations to papers are plausible measures of inventor awareness and use of scientific findings.

Arora et al. (2017) validate patent citations to science as a measure of knowledge flows using responses of industrial R&D lab managers to the Carnegie Mellon Survey (Cohen et al., 2000). Their validation exercise indicates a positive relationship between citations to science made by a firm's patents and the firm's reported use of science in its R&D process. Bikard and Marx (2020), in an attempt at understanding the process underlying patent citations to scientific literature, interview 21 inventors. In the interviews the inventors confirmed their direct involvement in the addition of citation to science to their patents, implying that the citation reflected their awareness of the cited publication. Finally, in a large scale analysis, Arora et al. (2020) propose a novel approach to understand the relationship between patent citations to science and the academic literature. They show a positive relationship between technological classes citing science and the average textual distance between the text of patents

[11] We winsorize patent values at the 1 and 99 percentiles. Categories are sourced from NBER patent classifications.

[12] For our analysis we use the matched sample with a confidence score above 7. See Marx and Fuegi (2019) for details

in the citing technological class and academic literature abstracts. Technological classes that are textually close to the academic literature have a higher propensity to cite scientific papers.

We create a binary indicator – *Science* – equal to one if the focal patent contains a front-page NPL citation linked to a scientific publication. Front page citations delimit legally the validity of the patent (Bryan et al., 2020). Further, the relative importance of front-page citations, over in-text citations, has increased over time. Front page citations as a share of overall citations to science went from 20% in 1970 to over 60% in 2019 (Marx and Fuegi, 2020). Approximately 26 % of patents cite science, and about 62% of the firms in our sample have been granted a patent that cites science. Of all the granted patent between 1980 and 2010, approximately 14% cite more than 1 publication, and on average a patent cites approximately 2 publications.

We classify different types of citations to science using a commonly used measure of journal quality, the Journal Impact Factor (JIF), as well as a new measure of the commercial relevance of the journal, developed by Bikard and Marx (2020): the Journal of Commercial Impact Factor (JCIF). The JIF and JCIF are calculated for each journal `J` and year `t` as the number of times the articles in `J` in years `t-1` and `t-2` were cited in year `t`, divided by the number of articles in `J` during years `t-1` and `t-2`. Whereas JIF employs citations from other papers, JCIF employs citations from patents. Approximately 34 % of patents citing at least one scientific publication, cite an article on a journal with a JIF in the top 2%, and 56 % of patents that cite a scientific publication cite on from a journal with a JCIF in the top 2%.

First to use science. The *PCS Data* includes about 3 million scientific publication that are cited in US granted patents. On average, a cited publication is cited by approximately 5.49 patent, while the median cited publication is cited by 2 patents, with a range from 1 to about 5,200 patents. In order to identify whether a patent was the first to cite a specific publication, amongst all USPTO patents, we compare each patent-cited publication with all the patents that cited the specific publication between 1901 and 2010. We classify the focal patent as first to use a given publication if no other patent that cited the publication was filed before the focal patent. Specifically, we classify patent `T` as first to use paper `S` if no other patent citing paper `S` was filed before `T`. Accordingly, *First Use of Science* is a binary variable equal to one if the focal patent is the first to cite a paper and zero otherwise. If a patent cites more than one publication, the first to use dummy variable receives the value of one if at least one of these articles are cited for the first time.

We build similar indices for citing scientific publications in different types of journals according the above described JIF and JCIF. We construct measures of first to use articles in top JIF and top JCIF by identifying whether a patent is first to cite a paper that was published in a journal with a JIF/JCIF above the 99th percentile.

Relevant science: Not all used discoveries are relevant for invention. Our theory assumes that internal absorptive capacity enables a firm to discern which discoveries will be relevant. Accordingly, we measure *relevant science* as publications that are highly cited by patents: papers that fall into the top 95th percentile of patent-to-science citations. We also construct a measure of *first to use relevant science* as a binary variable indicating whether a patent is the first to cite a relevant publication. As a robustness check We also present results with papers that have been cited more than once, *Mult Tech Use*, as relevant science.

Corporate participation in science. We obtain corporate publication activity from Arora et al. (2017).[13] The corporate publication data allows us to identify scientific papers for which at least one of the authors is affiliated with US headquartered Compustat firm. We thus create our main measure of a firm engagement in science: *Publication Stock* [14].

A key contribution of this paper is exploring the mechanisms by which corporate participation in science might contribute to developing a first mover advantage in using public

[13] Arora et al. (2017) match approximately 800 thousand scientific in the "Science Citation Index" and "Conference Proceedings Citation Index - Science" of Web of Science, published between 1980 and 2015, to their sample of Compustat firms; the details and data can be found in the appendix of Arora et al. (2017)

[14] *Publications Stock* and *Patent Stock* are calculated using a perpetual inventory method with a 15 percent depreciation rate δ, where $Publications\ Stock_t = Publications_t + (1 - \delta)\ Publications\ Stock_{t-1}$

science. We develop two measures using information in the corporate publication data. Building on Rosenberg (1990), who argues that active engagement in scientific research 'buys' firms a ticket for admission into an information network, we propose that attending conferences in which relevant science is presented and awareness of applicable journals raises a firm familiarity, and possibly reduces search costs, allowing for a timely implementation of the scientific advances.

Using corporate publications between 1980 and 2010, we identify conferences and journals with which a firm is "*familiar*" at each point in time. We construct two measures of familiarity with a conference or journal, one based on whether the firm has published in a conference's proceeding and one based on whether the firm has published in a journal. Specifically, we encode conference attendance by as firm `F` has attended conference `C` if at least one employee of `F` is among the affiliations in a paper in the proceeding of conference `C`. Similarly, at the journal level, we consider firm `F` to be familiar with a journal `J` if `F` has published in `J`. [15]

We use conference information disambiguated in Microsoft Academics. There are about 3500 conferences linked to scientific articles, 46% of which are linked to articles cited in the front page of patents. In our sample, 15% of the articles cited in patents are linked to a conference, 32 % of the patents citing science cite an article presented at a conference, while at the firm level the average firm cites articles in its patents that are linked to approximately 8 different conferences.

To conduct our analysis at the patent level we adapt the measure for each patent using the *PCS Data*. We classify the focal patent `P`, filed by firm `F` and citing a scientific journal `J`, as familiar with `J` if an employee of `F` has authored a paper published in `J`, prior to the filing of `P`. Similarly, at the conference attendance level, we indicate the focal patent `P`, filed by firm `F` and citing a paper published in the proceeding of conference `C`, as familiar with `C` if

[15] We use Microsoft Academics (MAG) Sinha et al. (2015) to identify the characteristics of each paper, such as the journal in which it was published, when it was published, what other papers it cites, and if it was presented at a conference. The *Corporate Pubs Data* from Arora et al. (2017) links Compustat firms to the Web of Science database (WoS). Since WoS and MAG use different identification codes for the same paper, we create a crosswalk between the WoS IDs in the *Corporate Pubs Data* and MAG IDs using TFIDF and fuzzy matching on papers' titles and authors, limiting comparisons within rolling windows of 3 years.

an employee of `F` has authored a paper presented at `C`.

Crowdedness. We use the number of patenting firms as a proxy of technological competition in a market. Specifically we count the number of firms (PERMCOs) that are assigned patents in the same primary CPC, up to the group level "CPC-6", in the same year.[16] As an alternative measure, we use the number of firms that cite at least one of the publications that are cited by the focal patent.

Patent Scope. We use two measures to proxy for patent scope: the length of the shortest independent claim, and the count of independent claims of the focal patent Marco et al. (2019).[17] More independent claims, or fewer words in the shortest independent claim, correspond to a broader patent scope.

3.2 Non-parametric results

We have theorized that competition lowers the average private value of using science in invention, and widens the gap between first-movers in the use of science and followers. In the empirical analysis, we test this. In addition, we empirically investigate whether firms that invest in research are more likely to be first-movers in using science, especially science that is likely to prove useful for invention. Finally, we explore the empirical basis for our conjecture that an important advantage from being a first-mover is the ability to obtain broader patents.

Our main sample and variables are at the patent level. The key variables for each patent are its dollar value to the firm, whether it cites science, and whether a citation to a specific scientific article first appeared in the focal patent. Table 2 presents descriptive statistics for our main variables. The median patent in our sample is valued at $7.98 millions (1982 prices). The median values of patents that cite science and that do not cite science are respectively

[16] We obtain primary CPC codes for each utility patent from Google Patents.

[17] Similar measures can also be used, for example Kuhn and Thompson (2019) propose the length of the first independent claim. The length of the shortest and the first independent claim, as well the average length, are highly correlated.

$9.14 million and $7.6 million.

The value of patents citing science *vs* not citing science, however, differs along an important dimension: how many firms are patenting in the same technological space. Figure 1 shows that as the number of firms patenting in a technological class increases the difference in value between patents citing science and patents that do not cite science steadily decreases.[18] This suggests that firms tend to create more value using scientific advances in less crowded technological fields, consistent with the idea that private returns to using science are low if rivals also have access to the same science.

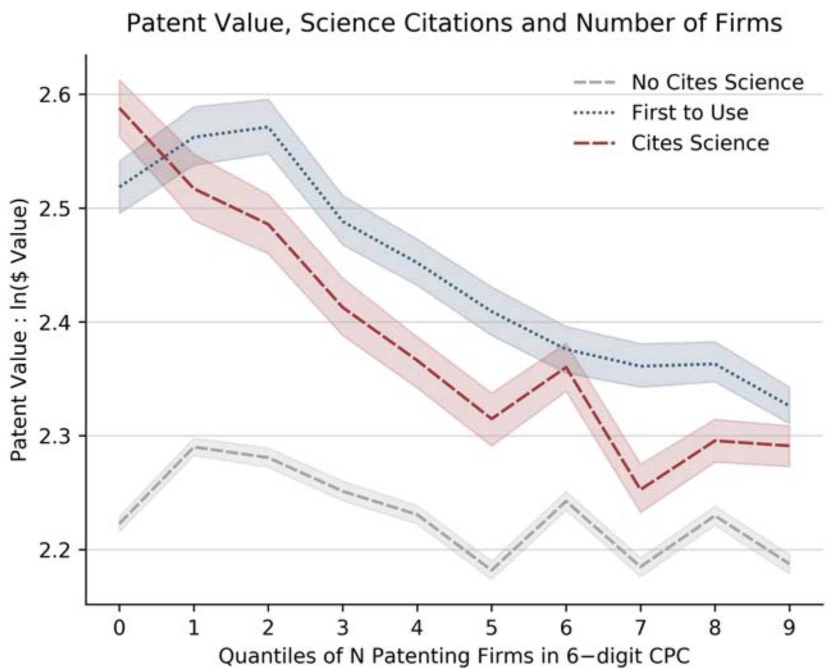
To explore first-mover-advantage in the use of science, we split the sample of patents citing science into patents that are first to use a scientific article and patents that only cite scientific articles previously cited by other patents.[19] First to use patents (blue, long-dashed line in Figure 1) are of higher value when there is more than one firm in a technological space. Additionally, the difference between being first to use (long-dashed blue line) and not first to use (short-dashed red line) tends to be larger in more crowded spaces. These trends suggest that the negative effect of competition are mitigated by being the first to use a particular research article.

Note also that our measure of first-use is absolute. It is possible that a follow-on use may, in fact, be the first use in the relevant market. If so, we are under-estimating the private value of first-use by mixing economically relevant first-use and follow-on use in a single category.

[18] The median patent is issued in a patent class ("CPC6") populated by 19 firms.

[19] If two patents are filed on the same day and they cite the same science, they are both first to use.

Figure 1: Use of Science in Crowded Spaces



This figure shows the average patent value for different bins of competition (Number of Firms Patenting in the 6-digit CPC); we group patents into 10 quantiles based on the number of patenting firms in the same CPC Group ("CPC6"), cut-offs are determined yearly. The values are presented for 3 different groups: (i) patents that do not cite science (medium-dashed, grey line) (ii) patents that cite science for the first time (long-dashed, blue line) and (iii) patents that cite science, but they don't do so for the first time (short-dashed, red line).

4 Econometric analysis

4.1 Patent value and the use of science

We estimate the following specification for the i^{th} patent of the k^{th} firm:

$$\ln(\xi_{ik}) = \alpha_0 + \alpha_1 Science_{ik} + \boldsymbol{Z}'_{ik}\boldsymbol{\gamma} + \epsilon_i \tag{1}$$

The value of the patent is represented by ξ_{ik} and $Science_{ik}$ is a dummy variable which takes the value 1 if the patent cites science, and 0 otherwise. We control for factors Z_{ik} that may influence the use of science and patent value. These include grant-year fixed effects, because the use of scientific papers in the front page of patents varies over time; the logarithm of the firm's market capitalization on the day prior to the issuing of the patent; firm size; patent class fixed effects to account for variation of the use of science across different technologies; and firm fixed effects to control for the presence of unobservable firm characteristics that do not vary over time. We cluster the standard errors by firm to account for potential serial correlation in the use of science within firms.

Table 3 presents the estimation results for the relationship between patent value and the use of science. The results show that patents that cite science are more valuable than patents that do not, but the difference is economically small. Column 1 presents estimates without controlling for firm fixed effects. The coefficient estimate of *Science Dummy* indicates that patents that cite scientific papers are about 3.8% more valuable than non-science citing patents. When controlling for firm-fixed effects, this estimate is cut by about two thirds and it is not statistically different from zero. The estimates in Column 2 imply that citing science, for the average patent, is associated with an increase in patent value of approximately \$ 212,000 and for the median we observe an an increase in patent value of approximately \$ 96,000 (in 1982 prices), relatively small differences when compared with the average value of a patent.

Columns 3-5, Table 3, explore heterogeneity by the quality of the cited publication. Column 3 includes a dummy that equals one for cited publications that are published in journals with an impact factor (JIF) in the upper 1% of all journals in Microsoft Academics. This dummy variable receives the value of zero for all other observations, so patents not citing science and patent citing science that is not in a top JIF are lumped in one category. The estimate indicates patents citing a top JIF publication are more valuable than patents citing lower ranked publications. Patents citing science published in higher commercial impact factor journals (JCIF) are not more valuable than those citing journals with lower JCIF. Finally, Column 5 includes the two different quality dummies in a single specification. The value of using science is never bigger than 4% (summing all use of science use dummies) with respect to the value of non-citing patents, even when the cited publication is published in a high impact journal.

If the observed (small) difference in the economic value of citing scientific publications, *vs* not, is driven by differences in intrinsic quality of the two groups then we would expect that small differences in the technical value as well (Hall et al., 2005; Nicholas, 2008). Columns 6-8 examine the relationship between science and technical importance, measured by forward citations. The estimate of the *Science Dummy* in Column 6 indicates that patents using science receive on average 20% more citations by follow-on inventions compare to patents not citing science. For the average patent in the sample it translate into approximately 2 more citations. When we consider the use of high quality science (science cited in journals with an impact factor on the upper 1%) the difference increases by about one more citation: citing science increases the number of forward citations by 31%. Column 8 reports a linear probability model in which being in the top 1% of forward citations, in a patent class-year, a "Home Run", is related the use of science. A patent that cites science, when evaluated at the average, has a 55% (0.00824 / .015) higher probability of being a home run. Overall the results from Table 3 indicate that while patents that cite science are technically more important, the private economic value of using science is relatively low.

Table 4 present estimates by technology fields. The results indicate that using science in patented inventions appears to be valuable only in the "drugs" and "chemicals" categories where the use of science is valued respectively at \$ 800,000 and \$ 350,000 (in 1982 prices). The estimates at the technology field level confirm that the basic pattern is robust: The use of a resource that is available to many is not a source of significant private economic value.

4.2 Competition and first to use

If the private value of commercializing scientific research is *economically* small because science is non-excludable and thus can be used by all, we would expect that the value of using science be lower in more crowded technical spaces. However, we would expect that in crowded niches, first mover would be more valuable. As theorized in section 2.4, and as figure 1, suggested, the average value of patents is smaller in crowded niches. However, the value of first-movers is higher than that of followers. Moreover, though both decline with competition, the difference between the two is higher in more crowded niches. That is, the value of being a first mover is greater in more crowded spaces. Here we verify that those findings are robust to controlling for time and firm characteristics, including time invariant firm effects. Accordingly, we estimate the following specification:

$$\begin{aligned}\ln(\xi_{ik}) = \alpha_0 + \alpha_1 Science_{ik} + \alpha_2 Science_{ik} \times \ln(Competitors_i) + \alpha_3 \ln(Competitors_i) \\ + \alpha_4 First\ to\ Use_{ik} \times \ln(Competitors_{ik}) + \boldsymbol{Z}'_{ik}\boldsymbol{\gamma} + \epsilon_{ik}\end{aligned} \tag{2}$$

We measure how crowded or competitive the niche is with the number of firms that patent in the same 6-digit CPCs as the focal patent within the same year the focal patent is granted. For ease of exposition, we label firms operating in the same technology niche (measured either as those patenting in the same 6-digit CPC) as competitors. The linear competition terms are included in $\boldsymbol{Z}_i$. Our interest is at α_2 , where we expect $\hat{\alpha_2} < 0$, that is, the private value of commercializing science falls in the number of firms that have access to the publications cited by the focal patent.

Table 5 Column 1 introduces our measures of competition: the natural log of one plus the number of different Compustat firms in the same 6-digit CPC as the focal patent. The estimate of the coefficient on competition is negative, and the estimate on the dummy for science is small and statistically indistinguishable from zero, consistent with the estimates earlier, such as Table 3, column 2.

Column 2 adds an interaction between science and competition. As expected, we see that $\hat{\alpha_2}$ is negative. The coefficient estimate on science dummy jumps to close to 7%, indicating a large increase in the private value of commercializing science in low-competition environments compared to the baseline results in Table 3. The private value of using science falls sharply with competition, dissipating when number of competitors reaches the top quartile of the distribution of the competitors variable. Thus, we confirm a substantial heterogeneity of the private value of using science by number of potential users, and link the low average private returns to public science to the relatively high average number of competitors.

Column 3 in Table 5 introduces our main variable of interest, which captures if a patent is the first to use a scientific paper. We test whether the negative effect of competition on private value can be mitigated by being a first-mover. In Column 3 we add an interaction term between first to use and competition. As expected, first to use substantially mitigates the negative effect of competition on the private returns to using science. The coefficient estimate on the interaction term between science and competition is reduced by half when science is first cited by the focal firm (from -0.02 to -0.0103). That is, as in the non-parametric analysis, we observe that being first allows for a reduction in the negative effect of competition by 50%. Columns 4-7 provide estimates by technology field. These are broadly consistent, showing that first to use mitigates the effect of competition in all fields, albeit that the effects are not always precisely measured. Drugs, however, appear to deviate from this pattern. The estimated interaction term is about half the size of that in Column 3, and of the opposite sign. This may reflect the high reliance on science in bio-pharmaceuticals, but may also reflect the somewhat special role of patents in protecting pharmaceutical inventions. For instance, though Merck was the first-mover in statins, Parke-Davis (and subsequently, Pfizer) was able to introduce a more effective product.

4.3 Patent Scope

As a direct test of the mechanism discussed in the theory, we investigate whether pioneering the use of scientific advances allows first movers to secure broader patents. We estimate, for the i^{th} patent of the k^{th} firm

$$Patent\ Scope_{ik} = \beta_0 + \beta_1 First\ to\ Use_{ik} + \boldsymbol{Z}'_{ik}\boldsymbol{\gamma} + \epsilon_{it} \tag{3}$$

Table 6 shows that patents that cite science have about 3% more independent claims (Column 1), but have about the same number of words in the shortest independent claims as patents that do not cite science (Column 3). However, being first to use is associated with 6% more independent claims on average (Column 1) and 4% fewer words in the shortest claim (Column 3). That is, compared to patents that do not cite science, patents of first movers have about 9% more independent claims. The gap between the patent scope of first movers and followers is even greater when considering the use of relevant science. Column 2 shows that the first mover patent have about 11% more independent claims on average compared to follower patents. Similarly, Column 4 shows that the length of the shortest independent claim is about 7% shorter for first mover patents relative to follower patents. In other words, one way in which being a first-mover in using science translates into private value is being able to get a broader patent, which can then discourage entry and provide a greater zone of exclusivity for the first mover.

4.4 Scientific capabilities and first to use

The foregoing results naturally raise the question of which firms are more likely to be first-movers in using science. The theory of absorptive capacity (Cohen and Levinthal, 1989) predicts that corporations that produce science increase their ability to recognise and apply scientific knowledge originated outside the firm's boundaries. We estimate the following specification for the i^{th} patent of the k^{th} firm:

$$First\ to\ Use_{ik} = \beta_0 + \beta_1 \ln(Publication\ Stock_k) + \boldsymbol{Z}'_{ik}\boldsymbol{\gamma} + \epsilon_{it} \tag{4}$$

where *First to use* is a binary variable equal to 1 when the focal patent is the first to cite a scientific paper; *Publication Stock* is the cumulative number of publications of the firm, which is calculated using a perpetual inventory method with a 15 percent depreciation rate δ, where $Publications\ Stock_t = Publications_t + (1 - \delta)\ Publications\ Stock_{t-1}$; Z includes our set of controls, such as the grant-year fixed effects, the firm's *Patent Stock* and *R&D Intensity* and firm fixed effects. We cluster the standard errors by firm to account for potential serial correlation in the use of science within firms.

Table 7 shows that a doubling of publication stock will increase the probability of being first to use by 1.8 percentage points, which, evaluated at the mean of the distribution of first to Use, translates into a 13% increase in the probability to be first to use. The estimated relative increase in the likelihood of being first to use ranges from 3% in Column 2 to approximately 24% when we consider first use of high quality science. This suggests that corporate engagement in upstream research increases a firm's ability to recognize extramural knowledge, where previous evidence was constrained to the use of R&D aggregate data.

4.5 Familiarity with science and first to use

The estimated relationship between publication activity and first to use raises questions about the underlying mechanisms through which engagement in scientific research allows firm to move more quickly into unexplored scientific areas. Active engagement in scientific research may raise a firms familiarity with relevant journals and conference proceedings. We explore whether this not only leads to citation to science, as Baruffaldi and Poege (2020) show, but more specifically, whether it is related to a firm being the first to use the science. We thus estimate the following specification for the i^{th} patent of the k^{th} firm.

$$First\ to\ Use_{ik} = \beta_0 + \beta_1 Familiarity\ with\ Science_{ik} + \boldsymbol{Z}'_{ik}\boldsymbol{\gamma} + \epsilon_{it} \tag{5}$$

We estimate the above specification at the patent level, for the sample of patent citing science, since both our dependent and main independent variable are constructed conditional on a patent citing a scientific article. *First use of Science* is a binary variable equal to 1 when the focal patent is the first to cite a scientific paper and *Familiarity with Science* is a measure, at the patent level, indicating whether the focal patent cites a scientific paper published in for a conference or in a journal where the firm has also published.[20] We control for firm, year and patent class fixed effects. If corporate participation in conferences and publications in certain journals increases a firm absorptive capacity, we would expect $\beta_1 > 0$.

The results are reported in Table 8. Column 1 presents a validation test. Using an linear probability model, we find that a patent that cites internal science is also more likely to cite a paper that is being cited for the first time. The estimates from column 1 imply that patents that make internal citations, i.e., a citation to papers published by an employee of the focal firm prior to the filing of the patent, have a 6.3% point higher probability to be first to use. Evaluated at the average of the distribution of *first to Use* this translate into an increase of the of approximately 12% (0.063 / 0.54).

Columns 2 to 5 explore how first use is related to familiarity with the science cited. As previously defined, familiarity relates to whether the assignee of the patent has published in the journal cited by the focal patent or if the assignee has attended the conferences cited in in the focal patent. Estimates in Column 2 show that if a firm is citing a paper presented at a conference it attended, then its patent is 12% more likely to be a first-user of science. Similarly, if a patent is citing a paper published in an outlet the firm has published in before the filing of the patent, then the patent is 5.5% more likely to be the first at citing a paper (Column 3). In sum, a patent that cites science from a familiar domain is also more likely to cite a paper that is being cited for the first time. Column 4 shows that familiarity through journals and familiarity through conference participation are largely independent in terms of their effects of first use. Column 5 and 6 in Table 8 consider the first use of papers published

[20] In unreported analysis we measure whether the focal patent cites a scientific paper published in a conference proceeding or in a journal which the firm *cited in its scientific research.* The resulting estimates are similar to the estimates in Table 8: familiarity with science increases the likelihood of a patent being first to use.

in journals with high journal impact factor (Column 5) and with a high commercial impact factor (Column 6); the estimates in Column 5 and 6 are in line with the baseline results.

We had assumed that absorptive capability implies that a firm is not only aware of scientific discoveries but is also able to assess, better than others, the relevance of the discovery for use in its inventive activities; we thus restrict our first to use measure to relevant science. In columns 7 and 8 of Table 8, we assess whether engagement in the publication process increases the likelihood of pioneering the use of papers (Column 7) that *will be* cited more than once – *First to Use Mult Tech Use* – or the use of papers (Column 8) that *will receive* enough citations to place them in the upper 5% percent of papers with respect to patent citations count – *First to Use Relevant Paper*. Evaluating our estimates at the average of the distribution of *First to Use - Mult Tech Use*, being familiar with the science used translates into an increase in the likelihood of being *First to Use - Mult Tech Use*, by 21% (0.0867 / 0.4). Similarly, at the average of the distribution of *First to Use - Relevant Paper*, being familiar with the science used translates into an increase in the likelihood of being *First to Use - Relevant Paper*, by 36% (0.0267 / 0.075).

5 Conclusion

Research suggests that corporations are reducing their engagement in performing scientific research (Arora et al., 2017). Sourcing outside knowledge is thus becoming ever more necessary, and scientific advances from public institutions have become a crucial input into the corporate innovation. However, creating private value from an input that is freely available to all, including competitors, is not straightforward. The resource based view suggests that creating private value requires idiosyncratic resources that are not reproducible by others and cannot be easily transferred (Barney, 1986). How then can firms create private value from public science?

In this paper we explore how by being the first to use scientific advances, firms can mitigate the negative effect that competition in the technical field has on value creation from public science. Our findings suggest that firms need to have the absorptive capacity to understand and use external knowledge, particularly when they cannot simply follow another firm's lead. Maintaining such a capability is likely to require a cadre of in-house scientists, who can plug into the relevant flows of scientific knowledge. The most effective way to remain plugged in to the scientific network is to be a participant in the research process.

Our findings raise a potential concern about the health of the American innovation ecosystem. While the growing specialization of universities in upstream research and of firms in downstream development should make each sector more productive in its respective activity, it also means that the need to link these two activities together is also becoming more important. If, by withdrawing from science corporations lose their ”ticket” to the scientific community, linking public science to downstream invention would be hard to maintain. How society can manage sufficient incentives to use public science in downstream invention in an ecosystem where firms gradually lose their ability to understand, and hence profit from, public science is a central challenge for policy makers and business managers alike.

References

Agarwal, R. and Gort, M. (1996). The evolution of markets and entry, exit and survival of firms. The review of Economics and Statistics, pages 489–498.

Ahmadpoor, M. and Jones, B. F. (2017). The dual frontier: Patented inventions and prior scientific advance. Science, 357(6351):583–587.

Arora, A., Belenzon, S., and Patacconi, A. (2018). The decline of science in corporate R&D. Strategic Management Journal, 39(1):3–32.

Arora, A., Belenzon, S., and Sheer, L. (2017). Back to basics: why do firms invest in research? Technical report, National Bureau of Economic Research.

Arora, A., Belenzon, S., and Suh, J. (2020). Science and the market for technology.

Arora, A. and Ceccagnoli, M. (2006). Patent protection, complementary assets, and firms' incentives for technology licensing. Management Science, 52(2):293–308.

Barney, J. B. (1986). Strategic factor markets: Expectations, luck, and business strategy. Management science, 32(10):1231–1241.

Baruffaldi, S. and Poege, F. (2020). A firm scientific community: Industry participation and knowledge diffusion. Max Planck Institute for Innovation & Competition Research Paper, (20-10).

Bikard, M. and Marx, M. (2020). Bridging academia and industry: How geographic hubs connect university science and corporate technology. Management Science, 66(8):3425–3443.

Bryan, K. A., Ozcan, Y., and Sampat, B. (2020). In-text patent citations: A user's guide. Research Policy, 49(4):103946.

Cohen, W. M. and Levinthal, D. A. (1989). Innovation and learning: the two faces of R & D. Economic Journal, 99(397):569–596.

Cohen, W. M., Nelson, R. R., and Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why us manufacturing firms patent (or not). Technical report, National Bureau of Economic Research.

Cohen, W. M., Nelson, R. R., and Walsh, J. P. (2002). Links and impacts: the influence of public research on industrial r&d. Management science, 48(1):1–23.

Endo, A. (2010). A historical perspective on the discovery of statins. Proceedings of the Japan Academy, Series B, 86(5):484–493.

Fabrizio, K. R. (2009). Absorptive capacity and the search for innovation. Research policy, 38(2):255–267.

Fleming, L., Greene, H., Li, G., Marx, M., and Yao, D. (2019). Government-funded research increasingly fuels innovation. Science, 364(6446):1139–1141.

Fleming, L. and Sorenson, O. (2004). Science as a map in technological search. Strategic management journal, 25(8-9):909–928.

Fosfuri, A., Lanzolla, G., and Suarez, F. F. (2013). Entry-timing strategies: The road ahead. Long Range Planning, 46(4-5):300–311.

Gambardella, A. (1992). Competitive advantages from in-house scientific research: The us pharmaceutical industry in the 1980s. Research policy, 21(5):391–407.

Gambardella, A. (1995). Science and innovation: The US pharmaceutical industry during the 1980s. Cambridge University Press.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. RAND Journal of economics, pages 16–38.

Helfat, C. E. (1994). Evolutionary trajectories in petroleum firm r&d. Management science, 40(12):1720–1747.

Helfat, C. E. and Lieberman, M. B. (2002). The birth of capabilities: market entry and the importance of pre-history. Industrial and corporate change, 11(4):725–760.

Jaffe, A. B. and Trajtenberg, M. (2002). Patents, citations, and innovations: A window on the knowledge economy. MIT press.

Jinha, A. E. (2010). Article 50 million: an estimate of the number of scholarly articles in existence. Learned Publishing, 23(3):258–263.

Klepper, S. (2002). The capabilities of new firms and the evolution of the us automobile industry. Industrial and corporate change, 11(4):645–666.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. The Quarterly Journal of Economics, 132(2):665–712.

Kuhn, J. M. and Thompson, N. C. (2019). How to measure and draw causal inferences with patent scope. International Journal of the Economics of Business, 26(1):5–38.

Lieberman, M. B. and Montgomery, D. B. (1988). First-mover advantages. Strategic management journal, 9(S1):41–58.

Lieberman, M. B. and Montgomery, D. B. (1998). First-mover (dis) advantages: retrospective and link with the resource-based view. Strategic management journal, 19(12):1111–1125.

Lieberman, M. B. and Montgomery, D. B. (2013). Conundra and progress: Research on entry order and performance. Long Range Planning, 46(4-5):312–324.

Mansfield, E. (1995). Academic research underlying industrial innovations: sources, characteristics, and financing. Review of Economics and Statistics, 77(1):55–65.

Marco, A. C., Sarnoff, J. D., and Charles, A. (2019). Patent claims and patent scope. Research Policy, 48(9):103790.

Marx, M. and Fuegi, A. (2019). Reliance on science in patenting. Available at SSRN.

Marx, M. and Fuegi, A. (2020). Reliance on science by inventors: Hybrid extraction of in-text patent-to-article citations. Technical report, National Bureau of Economic Research.

Mitchell, W. (1989). Whether and when? probability and timing of incumbents' entry into emerging industrial subfields. Administrative science quarterly, pages 208–230.

Mitchell, W. (1991). Dual clocks: Entry order influences on incumbent and newcomer market share and survival when specialized assets retain their value. Strategic Management Journal, 12(2):85–100.

Narin, F., Hamilton, K. S., and Olivastro, D. (1997). The increasing linkage between us technology and public science. Research policy, 26(3):317–330.

Nicholas, T. (2008). Does innovation cause stock market runups? evidence from the great crash. American Economic Review, 98(4):1370–96.

Poege, F., Harhoff, D., Gaessler, F., and Baruffaldi, S. (2019). Science quality and the value of inventions. Science advances, 5(12):eaay7323.

Poletti, M., LING, H., and ENGELLAND, B. (2008). An empirical study of launch order valuation based upon stock market reaction. Marketing Management Journal, 18(1).

Roach, M. and Cohen, W. M. (2013). Lens or prism? patent citations as a measure of knowledge flows from public research. Management Science, 59(2):504–525.

Rosenberg, N. (1990). Why do firms do basic research (with their own money)? Research policy, 19(2):165–174.

Roth, B. D. (2002). 1 the discovery and development of atorvastatin, a potent novel hypolipidemic agent. In Progress in medicinal chemistry, volume 40, pages 1–22. Elsevier.

Sauermann, Henry Cohen, W. (2010). What makes them tick? employee motives and firm innovation. Management Science, 56:2134–53.

Sinha, A., Shen, Z., Song, Y., Ma, H., Eide, D., Hsu, B.-j. P., and Wang, K. (2015). An overview of microsoft academic service (mas) and applications. In Proceedings of the 24th international conference on world wide web, pages 243–246. ACM.

Tripsas, M. (1997). Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry. Strategic Management Journal, 18(S1):119–142.

Watzinger, M. and Schnitzer, M. (2019). Standing on the shoulders of science.

Table 1: Variables Descriptions

Variable	Description
ln(Patent Value)	Value of the focal patent – in millions of USD, deflated to 1982 dollars using the Consumer Price Index – derived from abnormal stock returns of the filing company around the date of the patent grant. Measure for the *economic* value of the patent.
ln(1 + Fw Cites)	Number of citations the focal patent received up to 5 years from patent grant. Measure for the *technical* value of the patent.
Patent Home Run	Binary: the focal patent is in the upper 1% of citations received in that patent class/year.
ln(Mkt Cap)	Market capitalization of the focal patent's assignee (firm) the day before the issuing of the focal patent.
Science Dummy	Binary: the focal patent cites a scientific publication.
Sci Top JIF Dummy	Binary: the focal patent cites a scientific publication published in a journal in the upper 1% of Journal Impact Factor in that year.
Sci Top JCIF Dummy	Binary: the focal patent cites a scientific publication published in a journal in the upper 1% of Journal of Commercial Impact Factor in that year.
ln(N Patenting Firms)	Number of firms that file a patent in the same year as the filing of the focal patent.
First Use of Science	Binary: the focal patent is the first to cite a scientific publication.
Science Dummy (Relevant Paper)	Binary: the focal patent cites a scientific publication that in the upper 5% of patent citations to science
Self Citation	Binary: the focal patent cites a publication that was authored by an employee of the patent's assignee (firm) prior to the filing of the patent
Published in Journal	Binary: the focal patent is "familiar" with its own NPL science citations linked to a specific journal. the focal patent `T`, filed by firm `F` and citing a scientific journal `J`, is familiar with `J` if an employee of `F` has authored a paper published in `J` prior to the filing of `T`.
Attended Conference	Binary variable equal to one if the focal patent cites a scientific publication published in a conference proceeding attended by at least one employee of the patent assignee. Attendance to conferences is measure by publication in conference proceeding.

Table 2: Summary Statistics

Sample: Full	Mean	Median	75th	90th	SD	Min	Max	N
ln(Patent Value)	2.274	2.195	2.949	3.712	1.067	0.005	6.367	859206
ln(1 + Fw Cites)	1.296	1.386	1.946	2.565	0.948	0.000	6.724	870134
Home Run	0.015	0.000	0.000	0.000	0.122	0.000	1.000	869856
Science Dummy	0.258	0.000	1.000	1.000	0.438	0.000	1.000	870134
Science Dummy (High JIF)	0.052	0.000	0.000	0.000	0.222	0.000	1.000	870134
Science Dummy (High JCIF)	0.108	0.000	0.000	1.000	0.310	0.000	1.000	870134
ln(N Patenting Firms)	2.889	3.045	3.912	4.489	1.244	0.000	5.037	869856
First to Use	0.137	0.000	0.000	1.000	0.344	0.000	1.000	870134
First to Use (High JIF)	0.016	0.000	0.000	0.000	0.127	0.000	1.000	870134
First to Use (High JCIF)	0.038	0.000	0.000	0.000	0.191	0.000	1.000	870134
Science Dummy (Relevant Paper)	0.132	0.000	0.000	1.000	0.339	0.000	1.000	870134
First to Use (Relevant Paper)	0.019	0.000	0.000	0.000	0.138	0.000	1.000	870134
ln(N Indep Claims)	0.886	1.099	1.386	1.792	0.646	0.000	4.787	860116
ln(Words x Ind Claim)	4.729	4.779	5.147	5.481	0.666	0.000	9.444	860116
Self Citation	0.032	0.000	0.000	0.000	0.177	0.000	1.000	870134
Attended Conference	0.022	0.000	0.000	0.000	0.147	0.000	1.000	870134
Published in Journal	0.134	0.000	0.000	1.000	0.340	0.000	1.000	870134
ln(R&D Intensity)	0.104	0.056	0.117	0.176	0.256	0.000	10.154	839618
ln(Patent Stock)	7.850	8.315	9.528	10.349	2.213	0.693	11.185	870134
ln(1+Publication Stock)	6.230	6.645	8.509	9.366	2.801	0.000	10.922	870134
Mkt Cap	9.129	9.343	10.760	11.855	2.162	0.000	13.329	870134

Table 3: The Use of Science and the Patent Economic and Technical Value

Dependent Variable:	*log(Patent Value)*					*ln(1 + Fw Cites)*		*Home Run*
			J. Impact Factor	J. Comm Factor				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Science Dummy	0.0380	0.0121	0.00782	0.00587	0.00514	0.207	0.168	0.00824
	(0.00194)	(0.00683)	(0.00609)	(0.00444)	(0.00442)	(0.00702)	(0.00790)	(0.000669)
Science Dummy (High JIF)			0.0373		0.0327		0.0558	
			(0.0128)		(0.0102)		(0.0164)	
Science Dummy (High JCIF)				0.0177	0.00920		0.0938	
				(0.0113)	(0.0102)		(0.0122)	
Mkt Cap	0.335	0.597	0.597	0.597	0.597			
	(0.000394)	(0.0296)	(0.0296)	(0.0296)	(0.0296)			
Firm FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	858924	858368	858368	858368	858368	869288	869288	869288
Adjusted R^2	0.556	0.764	0.764	0.764	0.764	0.190	0.190	0.059
Avg Dep Var	2.27	2.27	2.27	2.27	2.27	1.29	1.29	.015

Notes: *log(Patent Value)* is the natural logarithm of the patent value (in USDm) derived from abnormal stock returns of the filing company around the date of the patent grant, sourced from Kogan et al. (2017). *Science Dummy High JIF* is a binary variable equal to one if the focal patent cites a scientific publication in the front page. *Science Dummy High JIF* is a binary variable equal to one if the focal patent cites a scientific publication published in a journal with a Journal Impact Factor above the 99th percentile within year. *Science Dummy High JCIF* is a binary variable equal to one if the focal patent cites a scientific publication published in a journal with a Journal of Commercial Impact Factor (sourced from Marx and Fuegi (2019)) above the 98th percentile within year. *ln(1+ Fw Cites)* is the natural logarithm of the number of forward citations within 5yr from the grant of the focal patent *Home Run* is a binary variable equal to one if the focal patent received a number of forward citations in the top 99th percentile among the patents granted in the same year and the same patent class CPC4. *log(Mkt Cap)* is the natural logarithm of the market capitalization of the focal firm the day before the patent was issued. Standard errors clustered at the firm level.

Table 4: Patent Value and Use of Science (Industry Level)

Dep Var: ln(Patent Value)	(1)	(2) ICT	(3) Electronics	(4) Drugs	(5) Chemical
Science Dummy	0.0121	-0.00780	0.00719	0.0278	0.0191
	(0.00683)	(0.00746)	(0.00819)	(0.00926)	(0.00788)
Mkt Cap	0.597	0.589	0.584	0.638	0.634
	(0.0296)	(0.0475)	(0.0443)	(0.0210)	(0.0252)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes
Observations	858368	258878	193945	70362	148110
Adjusted R^2	0.764	0.745	0.751	0.875	0.778
Avg Dep Var	2.27	2.35	2.10	2.55	2.35

Notes: *log(Patent Value)* is the natural logarithm of the patent value (in USDm) derived from abnormal stock returns of the filing company around the date of the patent grant, sourced from Kogan et al. (2017). *Science Dummy High JIF* is a binary variable equal to one if the focal patent cites a scientific publication in the front page. *log(Mkt Cap)* is the natural logarithm of the market capitalization of the focal firm the day before the patent was issued. Standard errors clustered at the firm level.

Table 5: Patent Value, Use of Science & Number of Patenting Firms

Dep Var: ln(Patent Value)	(1)	(2)	(3)	(4) ICT	(5) Electronics	(6) Drugs	(7) Chemical
Science Dummy	0.0125	0.0615	0.0767	0.0588	0.0389	-0.0134	0.0447
	(0.00691)	(0.0209)	(0.0221)	(0.0335)	(0.0217)	(0.0253)	(0.0191)
ln(N Patenting Firms)	-0.0386	-0.0346	-0.0347	-0.0173	-0.0219	-0.00892	-0.00835
	(0.0137)	(0.0126)	(0.0126)	(0.0159)	(0.00714)	(0.00591)	(0.00413)
ln(N Patenting Firms) x Science Dummy		-0.0152	-0.0207	-0.0174	-0.0122	0.0116	-0.0132
		(0.00545)	(0.00564)	(0.00888)	(0.00557)	(0.00847)	(0.00662)
First Use Science Dummy			-0.0278	-0.0583	-0.0133	0.0308	-0.0359
			(0.0115)	(0.0382)	(0.0182)	(0.0209)	(0.0158)
ln(N Patenting Firms) x First Use Science Dummy			0.0104	0.0152	0.0102	-0.00566	0.0198
			(0.00298)	(0.00842)	(0.00495)	(0.00672)	(0.00563)
Mkt Cap	0.598	0.598	0.598	0.589	0.585	0.638	0.634
	(0.0296)	(0.0296)	(0.0296)	(0.0475)	(0.0442)	(0.0210)	(0.0251)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	858368	858368	858368	258878	193945	70362	148110
Adjusted R^2	0.765	0.765	0.765	0.745	0.751	0.875	0.778
Avg Dep Var	2.275	2.275	2.275	2.35	2.1	2.55	2.35

Notes: *log(Patent Value)* is the natural logarithm of the patent value (in USDm) derived from abnormal stock returns of the filing company around the date of the patent grant, sourced from Kogan et al. (2017). *ln(N Patenting Firms)* is the natural logarithm of the number of firms patenting within a year and 6-digit CPC class *Science Dummy* is a binary variable equal to one if the focal patent cites a scientific publication in the front page *First Use Science Dummy* is a binary variable equal to one if the focal patent is the first to cite a scientific publication in the front page *log(Mkt Cap)* is the natural logarithm of the market capitalization of the focal firm the day before the patent was issued. Standard errors clustered at the firm level.

Table 6: First to Use and Patent Scope

	(1)	(2)	(3)	(4)
Dep Var: Patent Scope	ln(N Indep Claims)		ln(Words in Ind Claim)	
Science Dummy	0.0285	0.0103	0.000985	-0.0150
	(0.00437)	(0.00429)	(0.00552)	(0.00520)
First to Use	0.0607	0.0600	-0.0462	-0.0379
	(0.00532)	(0.00492)	(0.00567)	(0.00539)
Science Dummy (Relevant Paper)		0.0344		0.0286
		(0.00458)		(0.00721)
First to Use (Relevant Paper)		0.0525		-0.0195
		(0.00939)		(0.00936)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observations	859275	859275	859275	859275
Adjusted R^2	0.169	0.170	0.182	0.182
Avg Dep Var	.89	.89	4.73	4.73

Notes: *ln(N Indep Claims)* is the natural logarithm of the number of independent claims made by the focal patent *ln(Words in Ind Claim)* is the natural logarithm of the number of words of the shortest independent claim made by the focal patent *Science Dummy* is a binary variable equal to one if the focal patent cites a scientific publication in the front page *First Use Science Dummy* is a binary variable equal to one if the focal patent is the first to cite a scientific publication in the front page *Science Dummy (Relevant Paper)* is a binary variable equal to one if the focal patent cites a scientific publication that in the upper 5% of patent citations to science *First Use (Relevant Paper)* is a binary variable equal to one if the focal patent is the first to cite a scientific publication that in the upper 5% of patent citations to science

Table 7: Firms' participation in science and first to use

	Sample: Full	Sample: Citing Science		
	(1)	(2)	(3)	(4)
Dep Var: First to Use			High JIF	High JCIF
ln(1+Publication Stock)	0.0182	0.0176	0.0124	0.0349
	(0.00581)	(0.00919)	(0.00506)	(0.00948)
ln(Patent Stock)	-0.0252	-0.0429	-0.0173	-0.0363
	(0.00466)	(0.00817)	(0.00468)	(0.00662)
ln(R&D Intensity)	0.00947	-0.00121	0.00602	0.00415
	(0.00613)	(0.00671)	(0.00591)	(0.00653)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observations	838792	215994	215994	215994
Adjusted R^2	0.128	0.084	0.187	0.094
Avg Dep Var	.1368	.53	.0629	.1437

Notes: *First Use Science Dummy* is a binary variable equal to one if the focal patent is the first to cite, in its front page, a scientific publication *First Use High JIF* is a binary variable equal to one if the focal patent is the first to cite, in its front page, a scientific publication which was published in a journal with an impact factor in the top 1% in its field *First Use High JCIF* is a binary variable equal to one if the focal patent is the first to cite, in its front page, a scientific publication which was published in a journal with a commerical impact factor in the top 1% in its field *ln(1 + Publications Stock)* is the natural logarithm of the stock of scientific publications in which at least one of the authors is affiliated with the focal firm *ln(Patent Stock)* is the natural logarithm of the stock of patents of the focal firm *R&D Intensity* is the natural logarithm of R&D over Sales *Publications Stock* and *Patent Stock* are calculated using a perpetual inventory method with a 15 percent depreciation rate, where $\textit{Publications Stock}_t = \textit{Publications}_t + 75\%\textit{Publications Stock}_{t-1}$ Standard errors are clustered at the firm level.

Table 8: Firms' familiarity with science and first to use

Dep Var: First to Use Dummy	(1)	(2)	(3)	(4)	(5) High JIF	(6) High JCIF	(7) Mult Tech Use	(8) Relevant Paper
Self Citation	0.0634			0.0545	0.0401	0.0942	0.102	0.0535
	(0.00725)			(0.00759)	(0.00448)	(0.00962)	(0.00698)	(0.00473)
Attended Conference		0.122		0.114				
		(0.0111)		(0.0127)				
Published in Journal			0.0554	0.0515	0.0335	0.120	0.0867	0.0267
			(0.00921)	(0.00991)	(0.00423)	(0.00724)	(0.00760)	(0.00291)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	224192	224192	224192	224192	224192	224192	224192	224192
Adjusted R^2	0.086	0.088	0.086	0.091	0.192	0.124	0.062	0.047
Avg Dep Var	.53	.53	.53	.53	.06	.15	.4	.075

Notes: *First Use Science Dummy* is a binary variable equal to one if the focal patent is the first to cite, in its front page, a scientific publication *First Use High JIF* is a binary variable equal to one if the focal patent is the first to cite, in its front page, a scientific publication which was published in a journal with an impact factor in the top 1% in its field *First Use High JCIF* is a binary variable equal to one if the focal patent is the first to cite, in its front page, a scientific publication which was published in a journal with a commercial impact factor in the top 1% in its field *First Use Mult Tech Use* is a binary variable equal to one if the focal patent is the first to cite a scientific publication that is cited at least by two different patents *First Use High Tech Impact* is a binary variable equal to one if the focal patent is the first to cite a scientific publication that in the upper 5% of patent citations to science *Self Citation* is a binary variable equal to one if the focal patent cites a scientific publication authored by at least one employee of the patent assignee *Attended Conference* is a binary variable equal to one if the focal patent cites a scientific publication published in a conference proceeding attended by at least one employee of the patent assignee. Attendance to conferences is measure by publication in conference proceeding. *Published in Journal* is a binary variable equal to one if the focal patent cites a scientific publication published in a journal in which at least one employee of the patent assignee had published previous to the filing of the focal patent. Standard errors are clustered at the firm level.

Appendix

In the Appendix we show that the main results extend when absorptive capacity yields a noisy signal, and when competition directly affects payoffs. We also derive the conditions for a firm to invest in absorptive capacity.

Absorptive capacity provides a noisy signal

The firm with absorptive capacity receives a signal such that if the discovery is useful, the signal is positive with probability $\lambda > \frac{1}{2}$. Similarly, if the discovery is not useful, the signal is negative with probability λ. The probability of a positive signal, γ is given by $\gamma = p\lambda + (1-p)(1-\lambda)$. The probability of the discovery being useful given a positive signal, ϕ is given by $\phi = \dfrac{p\lambda}{p\lambda + (1-p)(1-\lambda)}$. Notice that $\phi > p$.

A fully informative signal (the case analysed in the text) implies $\lambda = 1$, which implies $\phi = 1$. A signal with no information implies $\lambda = \frac{1}{2}$, so that $\phi = p$. Suppose p is small enough such that $\dfrac{p^2 v^2}{c} - \Pi^o(N) < 0$. In this case, uninformed firms will prefer not to invest in the new discovery. However, if the potential first-mover, the firm with absorptive capacity, gets a sufficiently informative signal, it will invest. Formally, $\dfrac{v^2}{c} - \Pi^o(N) > 0$ implies that there is a λ large enough such that $\dfrac{\phi^2 v^2}{c} - \Pi^o(N) > 0$. Given a positive signal, the leader invests, with expected payoff $\dfrac{\phi^2 v^2}{2c}$. The ex ante payoff is therefore $\gamma \dfrac{\phi^2 v^2}{2c} + (1-\gamma)\Pi^o(N)$, which can be rewritten as $\gamma \left(\dfrac{\phi^2 v^2}{2c} - \Pi^o(N) \right) + \Pi^o(N)$. Potential followers will observe the outcome and invest in using the discovery if it is successful, which happens with probability $\gamma\phi\lambda$.

Investing in absorptive capacity

Suppose the cost of investing in absorptive capacity is F. For simplicity, let the signal be perfect, so $\lambda = 1$. If the firm, having invested in absorptive capacity (correctly) judges the discovery to be useful, its payoff is $\dfrac{v^2}{2c}$, an outcome which has probability p.[21] Thus the expected net benefit from investing in absorptive capacity is $p \left(\dfrac{v^2}{2c} - \Pi^o(N-n) \right) - F$.

The direct implication is that the payoff to investing in absorptive capacity is greater when there are more potential followers. Recall that the number of followers n increases with N. Thus, the payoff to investing in absorptive capacity is greater in more crowded niches.

[21] For simplicity, we assume that there will be exactly one discovery per period. If there are K discoveries, this is equivalent to assuming the fixed cost of absorptive capacity is $\frac{F}{K}$.