Back to Basics: Why do Firms Invest in Research?*

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Abstract

If scientific knowledge is a public good, why do firms invest in research? This paper revisits this question with new data on patent citations to corporate scientific publications. Using data on 4,736 firm for the period 1980-2006, we explore the relationship between the use of corporate research in invention and the output of corporate scientific publications. Our principal contribution is to document that corporate investment in research is closely related to its use in invention. Specifically, firms that build on their scientific publications in their inventive activity invest more in research than those that are less successful in using their research internally. Consistent with this, research that is internally used is valued more and is more productive.

Keywords: innovation, scientific research, development, use of science in inventions.

JEL Classification: O31, O32, O16.

1 Introduction

Although scientific knowledge is considered to be the quintessential public good, for-profit companies have contributed significantly to the production of scientific knowledge. In 2013, the business sector performed 24% of all basic research in the United States and funded a slightly larger share (NSF Science and Engineering Indicators, Table 4-3 2016). However, the share of basic and applied research in total business R&D expenditures has steadily declined over the last two decades (Mowery, 1009; Arora et al, 2015) To understand the causes and implications of such a decline, it is important to understand why firms invest in research in the first instance. In this paper, we use newly developed data linking patents to scientific publications matched to firms to investigate this question. In particular, we empirically study the extent to which corporate engagement in research, as measured by scientific papers published by corporate researchers, is related to the use of the research in invention, as measured by citations received

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by scientific publications of the firm from its own patents and from its rivals.[1] We find that firms produce scientific knowledge when they are able to use the findings. Put differently, scientific knowledge produced by firms is an important input for the eventual development of new products and processes.

American corporate labs initially had more modest goals. In the late 19th century, firms in technology intensive sectors such as railroads, steel, and telegraphy relied largely on external inventions. These firms established industrial labs to evaluate the quality of inputs, such as the quality of steel for rails (Mowery, 1995; Carlson, 2013). In the early 20th century, firms such as AT&T, GE and DuPont invested in internal research to solve production problems and evaluate and adapt inventions acquired from other firms (Reich, 1985; Hounshell and Smith, 1986). Corporate investment in research became more significant during the inter-war years, as corporations grew larger and more anxious to manage innovation instead of having to rely on the external inventions (Maclaurin, 1953). Stronger anti-trust enforcement provided an additional impetus as some farsighted managers saw in research a source of new products to fuel growth without running afoul of the anti-trust authorities.

The importance of discoveries such as vacuum tubes, radar, radio, synthetic rubber, nuclear fission, and penicillin, in the conduct of World War II led to a deeper appreciation of the potential economic usefulness of research. The simplest view of the role of research in innovation was the so-called linear model associated with Bush (1945), which asserted that technical progress rested upon scientific advance, that inventions grew out of research. This view was modified and enriched in a variety of ways (e.g., Kline and Rosenberg, 1986; David, Mowery and Steinmueller, 1992). However, the underlying notion that "... most of the actual research in industry is devoted to the development of new products or processes ... " (Griliches, 1986: 145) remained in place. Yet, because scientific discoveries are typically published and non-proprietary in nature (e.g., Dasgupta and David, 1994), why firms choose to invest in research themselves rather than free-ride on the research efforts by others remains unclear (Arrow, 1962; Rosenberg, 1990). This puzzle led to new explanations for why firms invest in research. These explanations focused on absorptive capacity to use external knowledge (Cohen and Levinthal, 1989; Gambardella, 1992), enhancing reputation to attract investors and costumers (Hicks, 1995) and incentives for high-skilled inventors (Audretsch and Stephan,

[1] Throughout, we use the term science and research interchangeably. The relevant distinction for us is that between the creation of new scientific knowledge and its use in invention.

1996; Stern, 2004; Gambardella et al., 2015). The various explanations are not mutually exclusive, but can have very different normative and positive implications. Moreover, there has been no serious attempt to explore empirically the extent to which firms produce scientific knowledge because it is relevant and useful for their own (downstream) inventions. [2]

Much of the existing literature on innovation has tended to focus on either R&D as a whole, conflating research and development, or patents, or knowledge and invention.[3] Data limitations are an obvious explanation. But insofar as technical advances draw upon scientific knowledge, understanding the production and use of science is important for both public policy and business strategy. Further, corporate investments in research have been a significant share of overall investment in research, and understanding why firms invest in research is useful not just for informing policy formulation but also for insights into how the economy itself is changing.

In this paper, we explicitly distinguish between research on the one hand, and downstream invention on the other. Our principal contribution is to document that corporate production of scientific knowledge is closely related to its use in internal invention. Specifically, firms that are able to build on their research in their inventive activity produce more knowledge than those that are less successful in using their research internally. Consistent with this, research that is internally used is valued more by investors and internal use is associated with higher R&D productivity.

Our main methodological contribution is to match publication records from ISI Web of Science to front-page non-patent literature (NPL) references on a large scale. While previous research using patent citation data was mostly done for selected industries and years (e.g., Narin and Noma, 1985; Narin et al., 1997; McMillan et al., 2000; Hicks et al., 2001; Breschi and Catalini, 2010; Bikard, 2015; Popp, 2016), our research examines a broad range of companies across many industries over a quarter of a century. Our primary firm sample consists of 4,736 U.S. headquartered publicly listed, R&D-performing companies over the period 1980-2006. Collectively, these firms account for 294,968 corporate scientific publications and make 266,361 patent citations to 50,494 corporate publications. This enables us to analyze the

[2] We use publication output as a proxy measure of the firm's investment in research. Implicitly, we are assuming that publication propensity is not changing over time. Though there are well documented instances of firms emphasizing patents over publications (see Hegde and Bhaskarbhatla 2014 on IBM), our reading of the evidence is that reduction in publications were also associated with a reduction in investment in upstream research relative to downstream development activities.

[3] Nelson (1959) was among the first to specifically analyze incentives to invest in research, as opposed to development. Griliches (1986) studied the returns to investment in research, as distinct from overall R&D.

relationships controlling for unobserved differences across firms or sectors. We use publications as a measure of the production of new scientific knowledge and patents as a measure of inventive activity. We treat a citation by a patent to a corporate publication as an indicator that the invention used or built upon the knowledge represented by the publication. Internal use is measured as a citation by a patent to scientific publication produced by the same firm.[4]

The firm behavior we analyze, namely the production and use of scientific knowledge by profit seeking companies, are complex. We are well aware that both the production and use of research are likely related to each other,potentially affected by common variables, some of which are unobserved and likely vary across firms and industries. We probe the robustness of the relationship between internal use and the production of scientific knowledge by using firm-fixed effects, by directly measuring organizational features that would help firms use internally developed science, and finally, by exploiting plausibly exogenous sources of variation in the extent of internal use.

The paper is organized as following. Section 2 discusses the related literature, Section 3 presents the data and empirical methodology, Section 4 presents the estimation results and Section 5 concludes.

2 Why do firms invest in research?

2.1 Scientific knowledge as an input into invention

In 1945 Vannevar Bush spelled out what became known as the Linear Model: "*Basic research leads to new knowledge. It provides scientific capital. It creates the fund from which the practical applications of knowledge must be drawn. New products and new processes do not appear full-grown. They are founded on new principles and new conceptions, which in turn are painstakingly developed by research in the purest realms of science.*" (p. 241) The linear model asserts a unidirectional link from science to technology development. [5]

Not only do advances in technology sometimes happen without corresponding advances in science,

[4] Citations to scientific publications and other types of non-patent literature are different from the citations to other patents. The latter constitute prior art and restrict the scope of the claimed invention.

[5] In 1969, The US Department of Defense challenged the linear model in its "Hindsight Project", which studied the contributions of research to the development of major weapon systems. The result of the study showed that only 0.3% of innovation came from "undirected" scientific research (i.e., basic research). On the other hand, The National Science Foundation, conducted the "TRACES Research Project" and found that 70% of the key events in the development of five technological innovations (magnetic ferrites, the video tape recorder, oral contraceptives, the electron microscope, and matrix isolation) were "nonmission-oriented" (i.e., basic research). (Mowery & Rosenberg, 1979).

sometimes to facilitate advances in science, by posing important puzzles, as well as by providing better tools for experimentation, measurement, and analysis (e.g., Gibbons and Johnston, 1975; Kline and Rosenberg, 1986; Rosenberg and Nelson, 1994; Narin, 1997)[6]. However, even if new products and processes are not mere outgrowths of research findings, research can be a useful input into invention. In a prescient analysis Nelson (1959) noted that even when inventions were not the direct result of scientific discoveries, scientific knowledge was valuable in guiding downstream development. David, Mowery and Steinmueller (1992) build upon this conception of scientific knowledge as a map for guiding downstream inventive activity. Fleming and Sorenson (2004) show that a patent that cites scientific publications receives more citations from future patents, especially when the focal patent is builds on highly inter-related components of knowledge, wherein trial-and-error is less efficient. In other words, scientific knowledge can be both directly valuable (the linear model) or indirectly valuable, by increasing the efficiency of downstream inventive activity.

Even so, it would still not imply that firms should individually invest in research. Indeed, Nelson (1959) and Arrow (1962) noted that scientific knowledge is a public good. Well before that, American firms such as AT&T, GE, and Du Pont had begun to invest in scientific research in the interwar years, and others followed suit after the war ended (Maclaurin, 1953). Moreover, the firms investing in research were apparently benefiting from it. In a seminal study, Griliches (1986) used the National Science Foundation (NSF) R&D-Census match, containing information on R&D expenditures, sales, employment, and other detail for approximately 1000 largest manufacturing firms from 1957 through 1977. He estimated a Cobb-Douglas production function, including basic research as a fraction of total R&D as a separate argument in addition to R&D stock, labor and capital. Griliches found a very large return to basic research – firms that spent a larger share of R&D on basic research were also more productive.[7] Since the results of basic research performed were typically published and shared, this raised the question of how firms were

[6] Gibbons and Johnson (1974) study the interaction between science and technology in the development of thirty inventions. They conclude that "it is apparent that the relationship between science and industrial technology is more complex than previously assumed by either scientists or economists; there exists a wide variety of potential forms of interaction. While this settles the issue of whether science contributes to technological innovation, and provides a justification, at one level at least, for maintaining an effective research capability, the very complexity of the relationship precludes simple calculations of the optimum size or distribution of the science budget." (Gibbons and Johnston, 1975 p. 241)

[7] Mansfield (1980) found that investment in basic research investment was related to productivity growth in US manufacturing industried between 1948-66, controlling for applied research and development. A similar relationship was found for a small sample of sixteen oil and chemical firms. If so, this suggested that the social returns (at the industry level) were similar to the private returns (at the firm level).

benefiting from their investment in research? We review next the literature that attempted to answer this question.

2.2 Absorptive capacity

Cohen and Levinthal (1989) challenged the public good nature of research, arguing that accessing outside knowledge is costly and requires absorptive capacity, which in turn requires that firms engage in R&D. Rosenberg (1990) also challenged the idea that existing knowledge, though in the public domain, was "on the shelf", available to all. Instead, he argued that finding, evaluating, and using publicly available knowledge itself presupposed some prior knowledge. He argued therefore that firms invest in research because, in part, basic research helps the company to stay up-to-date and identify scientific developments in its field as well as easily absorb external knowledge while fitting it to its own needs (Rosenberg 1990). A vast literature has found evidence consistent with absorptive capacity. Using survey data, Levin et al. (1987) find that independent R&D was most effective for learning about rival technology Gambardella (1992) shows that pharmaceutical firms with better research capabilities, measured by number of publications, are able to exploit internal as well as external science more effectively. Cockburn and Henderson (1998), using data from the pharmaceuticals industry, suggest that firms that want to take advantage of public research must invest in internal basic research as well as interact with public sector researchers.

2.3 Attracting talented inventors

Several studies have examined the role of corporate publications in attracting talented scientist-inventors. Hicks (1995) points out that one reason that companies not only perform research, but also publish results, is because publishing is an effective tool to recruit scientists[8]. Henderson and Cockburn (1994) emphasize the importance of corporate publication as a reward system. Examining research programs of major pharmaceutical firms they find that scientists that are promoted on the basis of their publications and reputation in the wider scientific community, generate more important patents. Some researchers may have a "taste for science" i.e., may be willing to accept industrial positions if allowed to spend some time on their own research and to publish it. Indeed, Stern (2004) finds that scientist may be willing to accept

[8] Cockburn and Henderson (1998) further suggest that participation in research "acts as a powerful recruiting tool, since the highest quality scientists in a field are often reluctant to work for private firms if they will not be able to publish and thus maintain their personal scientific reputation".

20% lower wages in exchange for autonomy, such as time for conducting and publishing independent research. Sauermann and Cohen (2010), study the relationship between industrial scientists' motives and their innovative activities, using survey data on PhD industrial scientists. They find that intellectual challenge and independence have the strongest (positive) relationship with innovative output, especially in upstream research activities.[9]

2.4 Signalling to consumers, investors, and regulators

Publications may also build a firm's reputation with regulators or customers. For instance, Lichtenberg (1986) shows based on Compustat firm data and defense-related federal procurement data that approximately half of the increase in private R&D investment between 1979 and 1984 was stimulated by increase in government demand. Audretsch and Stephan (1996) suggest that collaborative research with university scientists helps biotech firms signal their quality to the investors. Based on more than 30 years of publication data from European firms and the industry's productivity growth dispersion, Belenzon and Patacconi (2008) find that young firms, in highly developed financial markets, have stronger incentives to publish, in order to signal to prospective investors. Azoulay (2002) finds that prescriptions for anti-ulcer drugs respond to the publication by the drug manufacturer.

2.5 Back to basics: Scientific knowledge as an input

Although the arguments based on attracting researchers and signalling to outside stakeholders are plausible, they raise additional questions. For instance, why should a firm want to attract researchers? Similarly, why should outsiders see publication as a measure of quality relevant to them? Put differently, is investment in research similar to a peacock's tail, of no direct private value but helping the firm stand out from its competitors or is there direct private value as well?

In this paper we show that inventive activity in firms directly benefits from internally produced scientific knowledge. Firms that are able to build upon their research will invest in research, even though

[9] Gambardella et al. (2015) emphasize the role of autonomy as an effective incentive for knowledge workers. They develop a model that shows where the outcome and thus benefits for workers are uncertain. The allocation of decision rights over a project is an effective tool to motivate and increase efforts of scientist employees. They provide an example of DuPont that failed to hire reputed scientist whose salarly demands exceeded the firm's willingess to pay, and ended up recruiting the young Harvard scientist Wallace Carothers, by offering him independent research opportunities in the company. In this case, substituting salary by independent research successfully led to the invention of the Nylon. Gans, Murray and Stern (2014) develop a theoretical model in which a firm may allow researchers to publish because it lowers the wage cost, if it can effectively use patents to prevent the knowledge disclosed from benefiting rivals.

the knowledge itself is published openly. A firm may be able to move faster than its rivals in building upon its own research, some relevant details of the research findings may not be published, and many aspects remain tacit. In other words, consistent with Rosenberg (1990) and Cohen and Levinthal (1989), though published knowledge is potentially available to all, some firms may be better placed to use it, most notably the firm that produced the knowledge in the first instance. This sets up the first part of the empirical analysis where we test whether citations by patents to publications produced by the patenting firm are positively related to the firm's production of scientific knowledge. In a supplementary analysis, we also document that R&D productivity (as measured by patent output per unit of R&D investment) is greater for firms with greater internal use, controlling for the firm's publication stock.[10]

On the other hand, if rivals were able to use a firm's research, this would lower the private return, and hence the private incentives to invest in research (Gans, Murray and Stern, 2013). Hence, if patents by rivals were to cite a firm's publications, it would reduce the firm's willingness to invest. Thus, a follow up analysis examines how incentives to invest are related to the external use of internal science. Because citations may also reflect quality of the scientific output of the firm, we distinguish between citations by patents of rivals from citations by other external patents.[11] We find that use of its research by rivals is associated with lower production of publication output by a firm. These findings are mirrored by those for the implied value of publication stock. We estimate a Tobin Q regression which shows that the implied value of a firm's publication stock is greater when the publications are cited by its own patents but lower when the publications are cited by rivals.

Finally, we explore the factors that condition internal use. One way in which a firm is able to preferentially use its internal research is if the researchers are also involved in the invention process.

[10] The various explanations for why firms invest in research would all predict that invention productivity would be higher in firms that invest in research. For instance, insofar as the firm invests in research to attract talented inventors with a taste for science, one would also expect that talented inventors to also publish scientific articles, and for invention productivity to be higher in such firms. The absorptive capacity view has similar predictions if one makes the auxiliary assumption that inventors that are active in research are better able to absorb external knowledge, and hence, are more productive. What is distinctive is whether this coupling between research and invention is based on the more efficient use of internal knowledge or something else. The input view would imply that inventors would principally build on own their research.

[11] The signalling explanation arguably has the opposite implication. Publication is merely the price of impressing customers and investors, or mollifying regulators. The more widely research is cited, the more compelling a signal it is. The attracting talented researcher explanation would also tend not to predict a negative relationship between external citations and the value of internal research, because researchers would also care about their reputation with peers working for rival firms. The absorptive capacity explanation would imply no relationship between external use of internally generated science and the incentive to invest in science.

Such involvement might be helpful for aligning research priorities with downstream needs, help in the development of instruments, and generally facilitate the "back and forth" between the upstream research and the downstream development. We find the overlap between inventors and scientists of a firm to be positively associated with internal use.

We also exploit variation across and within states in legal doctrines that plausibly affect mobility of researchers, and therefore, are a plausibly exogenous source of variation in the ability of firms to build on internal research. A second source of variation in internal use arises from unexpected shocks to short-run profitability due to exchange rate movements. If investors (and hence, managers) are sensitive to short-run profits, the exchange rate movements that temporarily reduce profits can shift the composition of innovation projects in favor of those with shorter time-horizons. Insofar as short-term innovation are less likely to build upon research, this will reduce the demand for internal research. Both of these analyses indicate that the association between the production of scientific knowledge and its internal use is unlikely to reflect mere unobserved heterogeneity across firms. Instead, firms that expect to use the knowledge they produce are more likely to produce it.

3 Data

We combine data from three main sources: (i) company and accounting information from U.S. Compustat, (ii) scientific publications from Web of Science and (iii) patent and non-patent literature (NPL) citations from PatStat database. Building on Arora et al. (2015), we develop new data linking corporate publications to NPL citations to learn about the use the corporate science in invention, and the implication of this usage to corporate investment in research and stock market value.

We start with all publicly traded firms in the U.S. annual Compustat database from which we select companies with active records and positive R&D expenses for at least one year during our sample period, 1980-2006. We then exclude companies without at least one patent based on NBER 2006 patent dataset. We also exclude firms that are not headquartered in the United States. Our final estimation sample consists of an unbalanced panel with 4,736 firms and 57,765 firm-year observations over the period 1980-2006. Of those firms, 2,413 have at least one publication during 1980 and 2006.

Corporate publications. Similar to the method discussed in Arora et al. (2015), to identify a firm's participation in scientific research we match our sample firms to the Web of Science database (previously known as ISI Web of Knowledge). We include articles from journals covered in the "Science Citation Index" and "Conference Proceedings Citation Index - Science", which exclude social sciences, arts and humanities articles. Using the affiliation field for each publications record, we identify 294,968 articles, published between 1980 and 2006, with at least one author employed by our sample of Compustat firms, from more than 5000 different journals.

Patent citations to corporate science. The main methodological contribution of this paper is matching NPL citations to publications. Using all patents granted in the period 1980-2014 (including corporate and non-corporate patents), we perform a many-to-many match between each patent citation reference and the corporate publication data we identified from ISI Web of Science (approximately 14 million citations and 300 thousand corporate publications), allowing for more than one publication to be matched to each citation (based on a proximity score method explained in Appendix B). Next, to exclude mismatches, we use a more detailed matching algorithm that is based on different sources of publication information: standardized authors' names, number of authors listed, article title, journal name and year of publication. The matching algorithms accounts for misspelling, unstructured text, incomplete references, and other issues that may cause mismatches. An example of a front-page patent reference to non-patent literature is given in Appendix A (Figure A1). Finally, we perform extensive manual checks to confirm matches. More details on publication and citation matching are included in Appendix B.

Following the above procedures, we obtain 266,361 citations to 50,494 corporate science publications (17% of corporate publications), by 151,412 citing patents. Of the cited publications, 79% publications only have only external citations (i.e., never internal cited) while 21% have internal citations.

Ownership structures. While the matching of patents and publications is done at the subsidiary level, to better capture the complexity of large firms' innovative activities, which can typically be organized across subsidiaries (Arora et al., 2014), we aggregate to the ultimate-owner-parent-company level (UO) for our econometric analysis. For example, if a firm's subsidiary publishes scientific articles while the parent company is the assignee registered on the firm's patents, we capture both at the UO level. The construction of the firm dataset presents several challenges. We detail the challenges of constructing the dataset as well the procedures we use to deal with them in Appendix B.[12]

3.1 Descriptive statistics and non-parametric evidence

Our main sample and variables are at the parent company-year level. Table A1 in Appendix A summarizes the definition and data source for each variable. Table 1 summarizes descriptive statistics for our main variables over the sample period, 1980-2006. Our sample includes a wide distribution of firm sizes: market value ranging from 8 million dollars (10th percentile) to 3.2 billion dollars (90th percentile) and sales ranging from 2 million dollars (10th percentile) to 2 billion dollars (90th percentile).

Table 2 presents statistics for the main citation variables used in the econometric analysis for publishing firms. A total of 2,413 firms (51 percent of our sample firms) publish a scientific article at least once, 799 firms receive at least one citation to their publications (an average of 8 internal and 21 external citations per year). 388 firms make at least one citation to their own scientific publications (an average of 5.8 unique firm publications cited per year) and 760 firms receive at least one external citation to their publication (an average of 17 unique patents citing a firm's publications per year)

Table 3 presents mean comparison tests, within publishing firms, for differences in characteristics between firms with high and low internal use of their own science. Firms with above average value share of internal citations appear to have a higher publication count (0.4 vs. 0.2) as well as higher patent count (0.6 vs. 0.5) per R&D dollar. We also find that higher use of own science is associated with greater R&D intensity (0.2 vs. 0.1) and more overlap between inventors teams and authors (based on patents where the inventor team includes at least one author of a corporate publication published by the firm up to 3 years prior to the patent's grant year).

Insert Tables 1-3 here

3.1.1 Is corporate research an input into invention?

We examine whether corporate publications are more or less likely to be cited by a patent relative to comparable university publications. University publication were identified by matching a list of top 100 U.S. university names based on Shanghai Rankings to the affiliation field of each publications record. The

[12]For instance, a parent company and a subsidiary may have different identification numbers and records within the Compustat data. Furthermore, a single company may correspond to multiple firm identifiers within the Compustat database due to changes in ownership structure and accounting changes over the sample period.

sample includes publications from top universities that were covered in the "Science Citation Index" and "Conference Proceedings Citation Index - Science" between 1980 and 2006. Figure 1A presents mean comparison for university versus corporate publications by patent citations received per publication, showing a statistically significant higher average for corporate science (0.9 citations per publications for corporate publications versus 0.22 for university publications).

In general, a corporate publication is approximately 3 times more likely to be cited by a patent than is a university publication. Later, in the econometric analysis, we present the within-journal-issue analyses that also account for changes in sample composition, but with the same basic result, namely that corporate publications are more highly cited by patents than are university publications. Figure 1B plots the cumulative distribution of patent citations received per publication, by corporate and university publications. We find that the distribution of patent citations for corporate publications first-order stochastically dominates the distribution for university publication (p-value for Kolmogorov-Smirnov distribution equality test: $p<0.001$). In other words, for any citation level threshold, the share of corporate publications exceeding the threshold is higher than the corresponding share of university publications.

Insert Figure 1 here

3.1.2 The relationship between the use of research with publications and stock market value

Figure 2 presents the unconditional relationships between the use of science and firm investment in research and its stock market value. Figure 2A divides firms into two groups based on the citations the firm's publications received from its own patents as a share of citations received (by the firm's publications) from all patents. It shows that firms whose publications are disproportionately cited by its patents (above the median share of internal citations) also publish at a higher rate (an average of 3 publications per firm-year for low internal citation share versus an average of 28 publications for high internal citation share). Figure 2B shows that the way a firm's science is used is also related to its stock market value: Tobin's Q is positively related to internal use of science. Firm's with low internal citation share have on average a Tobin's Q ratio of 11, while firms with high internal share have a ratio of 12.5. These results are consistent with the view that corporate research is not merely useful for attracting talented researchers or signalling to investors or regulators but is also a valuable input for invention.

Insert Figure 2 here

4 Econometric analysis

4.1 The use of corporate research in invention

We begin our econometric analysis by comparing the contribution of corporate research and university research to invention. Table 4 presents OLS estimation results for the probability of a publication being cited by a patent, distinguishing between corporate and university publications. The sample comprises publications from top 100 U.S. universities and publications from our sample firms that were published between 1980 and 2006.[13]

The baseline results (Column 1) indicate that corporate research is more likely to be cited by patents than university research. The baseline probability of a publication being cited is only 2.5 percent. Evaluated at the sample mean, the probability that a corporate publication is cited by a patent is 11 percentage points higher than the corresponding probability for a university publication. This difference implies that a corporate publication is five and half times more likely to be cited by a patent than a university publication.

Corporate and university publications might vary in terms of their scientific importance, which can affect the likelihood that they are cited by a patent. Column 2 controls for publication importance using the number of citations the publication receives from other scientific publications. The number of citations received is normalized by average number of citations received by all publications appearing in the same year as the focal publication. Once we control for publication quality corporate publications become 13 percent points more likely to be cited by a patent relative to university patent. To mitigate concerns that the differences in patent citations to corporate and university publications are driven by research field, Column 3 presents estimates from a within-journal specification, where we compare patent citations to publications published in the same journal. The coefficient estimate on corporate publication falls to half of the estimate in the specification in Column 2, but remains statistically different from zero and

[13] The unit of observation is the publication. Corporate publication dummy is equal to one for articles with at least one author employed by the focal firm. The dependent variable, dummy for cited publication, is equal to one if a publication receives at least one citation from any patent, including patents filed by entitites not included in our sample.

large: Corporate publications are about three times more likely to be cited by patents than university publications published in the same journal. Column 4 restricts the sample of university publications to only those from the top ten US universities. The results in Column 4 indicate that corporate publications, controlling for number of citations and journal fixed-effects, have on average 6.2 percentage points higher probability to be cited by patents than publications from the top ten universities. In Column 5, we further control for variations within journals over time, by comparing publications in the same issue of the same journal (about 300,000 journal-issues), with very little change in the results relative to those reported in Column 3.

We further checked whether our findings are associated with higher self-citations to own publications. Column 6 excludes internal-citations of patents to own publications. Once we exclude self-citation, a corporate publication is 5.5 percentage points more likely to be cited, or about two and half times more, than a university publication. This reduction implies that the higher use of corporate research is partly driven by its internal use. One possible concern is that corporate publications are cited by lower quality patents than are university publications. Column 7 examines citations received from high quality patents – patents with above median number of citations received from other patents. The same pattern of results continues to hold for citations by high quality patents. Finally, Column 8 examines variation across technology fields. The technology field classification is based on the journal's subject category, and we interact field dummies with the corporate publication dummy. The results show that corporate publication are more likely to be cited than university publications in all technology fields (e.g., for energy: $0.06 - 0.021 = 0.039$).

In sum, our econometric analysis confirms the findings from Figure 1. Corporate publications are more likely to be cited by patents than publications from leading universities, even after controlling for journal-issue fixed effects. Insofar as patent citations proxy the use of research in invention, these results strongly support the view that corporate research is an important input into invention. We also find that the higher citation rates are driven partly by self-citations. Internal use is an important factor conditioning whether firms invest in research and thus we investigate internal use more fully next.

Insert Table 4 here

4.2 Internal use and publication output

Having shown that corporate science is an important input to invention, we turn next to examine how the way the firm's research is used is associated with publication output. Our main interest is to estimate the relationship between the internal use of research and future investment in research. We measure internal use of research as patent citations to own science and investment in research as the number of academic publications authored by at least one corporate scientist. Our baseline specification is as follows:

$$\ln(1 + Publications_{it}) = \beta_0 + \beta_1 \ln(1 + Self\_cites_{it-1}) + \mathbf{Z}'_{it-1}\gamma + \eta_i + \tau_t + \epsilon_{it} \qquad (1)$$

$Publications_{it}$ is the number of publications by firm i in year t. $Self\_cites_{it-1}$ is the number of patent citations made by firm i's patents that were granted up to year t-1 (inclusive) to its own scientific publications published up to year t-1 (inclusive). Our choice of the temporal structure of internal citations aims at mitigating concerns that number of publications and internal citations are affected by common temporal shocks (e.g., shocks to research opportunity that affect both the number of publications and patents that build on science). $\mathbf{Z}_{it-1}$ is a vector of firm-year controls, including citations-weighed patent stock, R&D stock, and sales. R&D stock is calculated using a perpetual inventory method with a 15 percent depreciation rate (Hall et al., 2005). So the R&D stock, GRD, in year t is $GRD_t = R_t + (1 - \delta)GRD_{t-1}$ where R_t is the R&D expenditure in year t and $\delta = 0.15$. Patent stock in year t is $Patent\ stock_t = Pat_t + (1 - \delta)Patent\ stock_{t-1}$ where Pat_t is the number of patents in year t, η_i and τ_t are complete sets of firm and year dummies, and ϵ_{it} is an *iid* error term. All specifications include a dummy variable for firm-year observations with zero publications.

Table 5 presents the estimation results. Columns 1-3 present the results for the relationship between internal citations – citations by patents filed by the firm to its own publications – and the number of publications the firm generates. Column 1 presents the results from a pooled specification. We find a positive and statistically significant relationship between internal citations and publications. The estimates imply that a one percent increase in internal self-citation is associated with a 10.4 percent increase in publication per year. Column 2 shows the same pattern of results when collapsing the panel data to a cross-section by averaging variables at the firm level. The estimates indicate that a one percent increase in internal citation is associated with about 16 percent increase in the flow of publication per year.

Column 3 introduces firm fixed-effects into the specification. The coefficient estimate on internal citation falls sharply from 10.4 to 1.6, indicating the relationship between internal citations and publication output is driven to a large extent by heterogeneity across firms. However, the within-firm coefficient estimate on internal citation remains statistically significant at the 1 percent level. The estimate implies that a one percent increase in internal citation is associated with about 1.6 percent increase in publication per year. Column 4 further restricts the sample to firms that publish, yielding a very small decline in the estimated coefficient of internal citations. Using the share of internal citations in total citations received by the firm's publications as a measure of internal use, as in Column 5, yields a similar relationship.

Insert Table 5 here

4.3 Knowledge spillovers and publication output

If firms invest in research as an input into internal inventive activity, then the use of that research by rivals would lower the return to such investments. We therefore investigate how investment is research is related to external citations – citations by outsiders to research by the focal firm.

Column 1 in Table 6 adds external citations to the focal-firm's publications to the specification in Column 3, Table 5. If the use of research by outsiders reduces the potential profits created by the research, private returns to research should be reduced by its outside use (Nelson, 1959; Arrow, 1962; Rosenberg, 1990). Our findings are consistent with this prediction. Column 1 presents a negative and statistically significant coefficient estimate on external citations. Based on this estimate, a 10 percent increase in external citation is associated with a 1.3 percent reduction in publication. The coefficient estimate on internal citations remains robust and similar in size to the estimate obtained from the within-firm specification in Table 5, Column3.

Not all citations represent profit-reducing spillovers. Indeed, citations from patents of firms that do not compete with the focal firm in the product market will not reduce the returns to the firm's investments in research, and may also reflect unobserved differences in the usefulness of the research findings. We build on Bloom et al. (2013) and Jaffe (1988), to construct SEGMENT and TECH, as empirical measures of how close the citing firm is to the cited firm in the product space and technology space, respectively.

Firms are close in the product space if the distribution of sales across different product market segment is similar. Firms are close in the technology space if the distribution of patents across patent classes are similar. Formally, the distance in the technology space is the angular distance (sometimes called the cosine distance) between the vectors representing the share of patents in various IPC classes for any pair of firms. Product market distance is measured analogously using SIC segments instead of IPC classes.[14] The correlation between SEGMENT and TECH proximity for the pairs of citing and cited companies in our sample is 0.0198, indicating that the measures proxy for different underlying variables. We compute external citation counts weighted by the SEGMENT and TECH proximity of the citing and cited companies.

Column 2 in Table 6 reports external citation count to a firm's own research separately weighted by SEGMENT and TECH proximity. While the coefficient for external citations weighted by TECH proximity is statistically zero, the estimate for external citation weighted by SEGMENT proximity is negative and statistically significant. The coefficient estimate on SEGMENT proximity indicates that a 10 percent increase in external citation by product market rivals is associated with a similar percent reduction in publication. The coefficient estimate on internal citation stock remains positive and statistically significant at 1% level. Results are even stronger when conditioning the sample on firms that publish: a 10 percent increase in external citations by product market rivals is associated with a 12 percent reduction in publication (Column 3). These results suggest that investment in research is negatively related to its use by rivals in downstream product markets.

Overall, the results in Tables 5 and 6 are consistent with the notion that a firm's investment in research depends, among other things, on how the research is used, both internally and externally. Specifically, a firm whose research is used in its own inventive activity is likely to continue investing in research. However, a firm whose research spills over to rivals is likely to reduce its investment. Furthermore, the

[14] The SEGMENT proximity is computed based on the absolute un-centered correlation distance between publication-cited firms and corporate patent-citing firm's sales share distribution across line of business listed within the Compustat operating segments database: $\left| \frac{\sum_{l=1}^{n} x_{jl} x_{j\prime l}}{\sqrt{\left(\sum_{l=1}^{n} x_{jl}^2\right)}\sqrt{\left(\sum_{l=1}^{n} x_{j\prime l}^2\right)}} \right|$

where "x_{jl}" denotes the share of sales of firm j in segment l.The measure ranges from zero (least correlated) to 1 (fully correlated). Similarly, the TECH proximity is computed based on each firm's patent share distribution across different technology fields (i.e., IPC). More details on the SEGMENT and TECH measures are included in Appendix B.

observed pattern of result is broad-based, and not driven by any particular industry[15].

Insert Table 6 here

4.4 Internal use and patent production

A more conventional method of demonstrating that research is a direct input into internal inventive activity inside firms is by estimating a patent production function as a function of R&D stock. All explanations for why firms invest in research would predict that research would increase inventive output, all else held constant. However, if research is a direct input into invention, then a distinctive prediction is that inventive output would be greater with greater internal use.

In Table 7 we use the annual flow of patents produced over the sample period (1980-2006), weighted by the citations each patent received up to 2014, as a function of the lagged R&D stock. Following standard practice, we take natural logs of both variables. We use the ratio of citations received from own patents to citations received from all patents as a measure of internal use. Column 1 and 2 confirm that investment in R&D is positively related to inventive output. The within-firm specification (Column 2) indicates that a 10 percent increase in R&D stock is associated with 1.6 percent increase in citation-weighted patents.

In Columns 3-4 we interact R&D stock with share of internal citation. In Column 3 we control for unobserved heterogeneity by using firm and year fixed effects and find that R&D is more productive when internal use is higher. The coefficient estimate on the interaction between R&D stock and internal citation share is positive and statistically significant. The estimate implies that for a two standard deviation increase in internal citation share, the elasticity of patent flow with respect to R&D stock increased by approximately 17% (relative to the mean). In Column 4 we receive similar results for the set of firms with at least one publication.

These results are consistent with earlier findings that internal use is associated with more investment in research. They indicate that one possible mechanism is that internal use implies a greater productivity of R&D investment as measured by the number of citation-weighted patents produced for a given level

[15] Tables A3 explores how the above pattern of results varies across main industries. Appendix A2 includes a list of all four-digit SIC codes that fall in each industry. Overall, we find that the results reported in Table 6 are present in most industries except for pharmaceuticals and biotechnology, where we have an insignificant coefficient for internal citation and a statistically significant positive coefficient for external citations to own science. The positive coefficient on internal citation is the highest for Machinery & equipment firms.

of R&D. In turn, this suggests that internal research either directly leads to inventions or indirectly by improving the focus of inventive efforts. In either case, the research is acknowledged in citations by the resulting patents. Firms that are able to use this research should generate more (or better quality) patents from a given R&D investment.

Insert Table 7 here

4.5 Internal use and stock market value

If, as we have argued, internal use increases the return to investment in research, whereas spillovers to rivals reduces such returns, this should be reflected not only in the level of publication output, but also its value. We therefore examine next the relationship between use of research and firm stock market value. Following Griliches (1986) and Hall et al. (2005), we estimate the following specification:

$$\ln(Tobin\prime s\ Q_{it}) = \alpha_0 + \alpha_1 \frac{Self\_cites_{it-1}}{Assets_{it-1}} + \alpha_2 \frac{External\_cites_{it-1}}{Assets_{it-1}} + \mathbf{Z}'_{it-1}\gamma + \eta_i + \tau_t + \epsilon_{it} \qquad (2)$$

In equation (2), market value is defined as the sum of the values of common stock, preferred stock, and total debt net of current assets. The book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles other than R&D. The dependent variable is the natural log of Tobin's Q, defined as the ratio of enterprise value to assets. **Z** is a vector of controls including lagged R&D over assets and patent stock over assets.

Table 8 presents the estimation results. The coefficient estimates in such a regression are amenable to different interpretations. We interpret these coefficients as reflecting the imputed value attributable to the relevant asset, or a "shadow price" of the asset (Hall et al., 2005). Column 1 in Table 8 includes 327 four-digit industry dummies (fixed effects) and columns 2-5 include firm fixed effects instead of industry fixed effects. Consistent with the results reported in Tables 5, 6 and 7, Column 1 and 2 of Table 8 indicate that internal citation to own publications is associated with a higher "shadow price" of publication stock. The within-firm estimate of the coefficient on internal citation stock (Column 2) indicates that a one standard deviation increase in internal citation stock to assets is associated with a 4% increase in Tobin's Q.

Column 3, adds external cites (citations by external patents to the firm's publications) to the specification. While the coefficient estimate on internal citation stock remains positive and statistically significant at 1% level, we find a positive and significant effect for external use of corporate research on its value.

Column 4 shows that for firms with at least one publication the coefficient on external citation drops in size and statistical significance. The coefficient on internal citations remains large and statistically significant. Columns 5 distinguishes citations received from rivals in product markets and those from other firms in the same technical domains. Column 5 indicates, similar to the findings in Table 6, that stock market value is negatively related to its external use by product market rivals. The coefficient estimate indicates that a one standard deviation increase in segment weighted external citation stock to assets is associated with a 8% decrease in Tobin's Q. In sum, internal use of research is associated with higher value whereas research that is used externally is less valuable.

Insert Table 8 here

4.6 Exploring the determinants of internal use

4.6.1 Science dependence, alignment, and organizational overlap.

Various factors determine the extent to which the flow of scientific knowledge produced by the firm is used in its downstream activities. One is how broad and far-ranging the firm's search for innovations is. Incremental improvements in existing products are less likely to use science than ones advanced beyond the existing technological frontier. In other words, one determinant of the use of internal science is simply the use of science in general. Factors that shorten the time horizon of managers will reduce use of science in general and internal use in particular. If line managers, responsible for choosing between incremental and radical innovations, respond to temporary declines in profitability by cutting back on longer horizon and uncertain exploratory projects, the derived demand for internal science will be lower. Such short-termism has been extensively documented in the finance literature as a response to the importance of meeting earning targets in publicly traded firms (Graham et al., 2004). This suggests the use of shocks to short-term profitability as a source of exogenous variation in internal use of science.

Internally produced scientific knowledge is more likely to be used if it is of high quality and aligned to the innovation strategy of the firm.[16] Alignment is difficult to achieve because it is difficult to determine and then ensure scientists undertake research that will produce knowledge that is useful for the firm. Scientists may take time to learn about the firm's needs, and their professional and intellectual interests may push them towards research more likely to make a splash rather than useful to the firm. Longer tenure for scientists can help align incentives and also help them understand what types of knowledge is useful to the firm. Legal restraints of labor mobility, which make it easier for firms to hold on to valuable researchers We use variation over time in the Inevitable Disclosure Doctrine (IDD) status at the state-year level as a second source of exogenous variation in internal use.

A third determinant is related to the internal organization of R&D. Kline and Rosenberg (1986) argued that innovation rarely proceeds linearly from knowledge creation to invention. Rather, innovations often require a "back-and-forth" between downstream invention and development activities and the more upstream research. As Rosenberg (1990:1970) put it: "*When basic research in industry is isolated from the rest of the firm, whether organizationally or geographically, it is likely to become sterile and unproductive. The history of basic research in industry suggests that it is likely to be most effective when it is highly interactive with the work, or the concerns of applied scientists and engineers.*" This suggests that organizational overlap between inventors and researchers should be associated with greater internal use. We compute a measure of overlap patent share as the share of patents per year where the inventor team includes at least one author of a publication (published by the firm) in the three years prior to the patent's grant year. Naturally, overlap patent share is only defined for firms with at least one publication.[17]

4.6.2 Organizational overlap between research and invention

Table 9 presents OLS estimation results for the relationship between overlap patent share and internal and external citation to research. In Columns 1–2 we estimate a linear probability model in which the dependent variable is equal to one if the firm receives at least one internal citation in the focal year to any of its publication published up to the focal year and zero otherwise. Column 1 includes four-digit industry fixed effects and Column 2 includes firm fixed effects. The results in Column 1 and 2 indicate

[16] The well known case of Xerox PARC, where the knowledge produced by Xerox researchers was not used by Xerox itself, shows the importance of alignment between research and innovation strategy.

[17] The average value of overlap pat share is 0.2 median is 0, standard deviation is 0.3 and the 10th and 90th percentile values are 0 and 1, respectively.

a higher probability of a publication being internally cited for higher overlap patent shares. Column 1 indicates that a two standard deviation increase in overlap patent share will increase the probability of internal citation by 8 percentage points. The within-firm estimate of the coefficient on overlap patent share (Column 2), falls by approximately 50% compared to the specification in Column 1, but remains statistically different from zero and meaningful.

In Column 3 the dependent variable is a dummy for at least one external citation in the focal year to the firm's prior publications. The coefficient on overlap patent share is negative, indicating that there is a negative relationship between overlap of inventor and research teams within the firm and external citations to the firm's publications.

For Columns 4 and 5 we use a specification where the dependent variable is internal citation share with industry and firm fixed effects, respectively. We find that results also hold with this alternative at 1% level. As a robustness check, in Column 6 we compute internal citation share including only citations to publications up to five years old. The coefficient estimate on overlap patent share remains robust and is even bigger in size compared to the estimate obtained from the complete sample (an estimate of 0.047 versus 0.038 for the complete sample). This is reassuring because our measure of overlap is based on an inventor authoring a corporate publication in the preceding three years. Therefore, confining attention to internal patent citations to more recent publications should result in a larger estimate, as is indeed the case.

In column 7, the analysis is at the level of the patent. The dependent variable is a dummy for whether a given patent cites an internal publication as a function of whether at least one of the inventors of that patent authored a corporate publication in the preceding three years. Even after controlling for the stock of publications and firm-fixed-effects, we find that the probability of an internal citation by a patent is positively related to the overlap between inventors and researchers. We conclude that a tight relationship between the research and invention teams is positively related to the internal use of a firm's science in its inventions.

Insert Table 9 here

4.7 Instrumental variable estimation

A possible concern with the results presented thus far is that the ability to use research internally as well as investment in research are both driven by a common unobserved variables. We have presented results using firm-fixed effects to mitigate concerns that these unobserved variables are persistent firm specific ones, such as differences in the quality of researchers. We now turn to estimates using two sources of exogenous variation to mitigate concerns about biases induced by time varying sources of unobserved heterogeneity, such as unobserved differences in demand or changes in technical opportunity. The IV estimation is motivated by more than a desire for causal estimates. Rather, each instrument is related to a potential determinant of internal use. In other words, although we cannot do justice to the issue, the analysis that follows also points to a mechanism linking the external environment of the firm and its use of internally generated science.

4.7.1 Inevitable Disclosure Doctrine

Our first instrument exploits variation over time and across states in the Inevitable Disclosure Doctrine (IDD) status at the state-year level as an instrument for internal use. Higher IDD restricts scientists' and inventors' mobility between companies (Klasa et al., 2015; Marx et al. , 2009).[18] Lower mobility should lead to longer tenures for scientists and inventors. In turn, longer tenures should improve alignment between research and invention activities. Lower mobility should also improve information flows between research and downstream activities. In particular, a firm would be in a better position to use its own research if it learns of promising findings earlier than rivals. A firm would also be in a better position to capitalize on its own research if some aspects of the research findings are tacit, and most easily transmitted through face-to-face interactions.

The identifying assumption is that policy imposed barriers to researcher mobility do not directly affect incentives to invest in research, such as by affecting wages of researchers. Further, one has to assume that the adoption of IDD is uncorrelated with unobserved state-specific variables that may also affect

[18] IDD effective years for relevant states, based on Klasa, Sandy, et al. (2015), are presented in appendix A4. The relevant state for each firm-year is determined using the majority publishing-state in each cohort (1985-1995 and 1996-2006), based on the publication's "Address" field. Example of firm-year observations in our sample with effective IDD: MA (4,246 obs.), MN (2,292 obs.), WA (1058 obs.), NC (946 obs.). The correlation between internal citations (of pubs up to 5 years old) and dummy for effective IDD in the previous year is 0.03.

incentives to invest in research.

For this analysis, the sample is conditioned on at least one publication and internal citations include only citations made to recent publications (up to five years old), under the assumption that we are interested in publications of current workers who are affected by the IDD status. The dummy variable, IDD, is equal to one if the Inevitable Disclosure Doctrine was effective in the state in that year. We control for state level employment, based on U.S. Bureau of Economic Analysis (BEA), to capture state characteristic that may have influenced the outcome independently of the IDD status.

Table 10 presents the estimation results. In the first stage result (Column 1), internal citation of recent publications is regressed on IDD status in the previous year at the focal state and the additional level controls. The results confirm our prediction that adoption of IDD in the state is positively related to internal use and that it is not a weak instrument (Kleibergen-Paap F statistic=21). Column 3 presents IV estimation results using two-stage least squares for the relationship between internal citations to firm's recent publications and science for the period 1985-2006. The coefficient estimate on internal citation increases from 1 (OLS estimation, Column 2) to 2. Based on the coefficient, a 10% increase in internal citation is associated with approximately 20% increase in publication per year.

In sum, instrumenting for internal use of research using policy induced variation in employee mobility yields coefficient estimates similar to those with firm-fixed-effects. These results are consistent with the view that firms that are able to use their research to produce inventions are more likely to invest in research.

Insert Table 10 here

4.7.2 Profit shocks due to exchange rate fluctuations

A different source of variation in internal use arises from changes in the mix of downstream innovation activities. Whereas incremental innovation is less likely to use science, including internally generated science, exploratory innovation is more likely to build on scientific advances and be guided by them. Exploration has more uncertain outcomes and is less likely during lean times. Put differently, exploratory innovation requires financial slack, because "slack provides a source of funds for innovations that would not be approved in the case of scarcity" (Cyert and March, 1963, p. 279). The opposite relationship has been argued between slack and exploitation. Exploitative innovation, also called ‘problemistic search’, is directed towards finding an immediate solution to a specific problem (Levinthal and March, 1981; March, 1991; Greve, 2003, 2007; Bruneel et al., 2016). For example, Bruneel et al. (2016), building on survey data from 2002-2006, find that high levels of financial slack (measured by level of cash) are associated with UK firms’ engagement in explorative knowledge sourcing from universities, whereas low levels of slack are associated with exploitative knowledge sourcing. Moreover, consistent with the ’slack search’ view, Graham at al. (2004) report that 80% of the 401 executive they surveyed would decrease their discretionary R&D spending and delay starting a new project in order to meet an earning target.

We exploit financial shocks using foreign currency devaluations for export-oriented American firms. When dollar-denominated profits drop due to a stronger US dollar (USD), firms would engage in more exploitation and less exploration. Assuming that exploitation builds less on science, we expect less internal use of research (that is, patent citations to own science) as firm patents become more exploitative and less exploratory. The main idea is that exchange rates affect profits of firms with foreign subsidiaries, and profits in turn affect the decision of firms to exploit science. Our identifying assumption is that short-term profit shocks affect the decision of firms to use science, but short-term profit shock does not affect the value of scientific research independently from its effect of the use of research. Specifically, we assume that (i) the future profits depend upon the realized level of exchange rates, so that conditioning on current exchange rates, the long run value of research is unaffected for a given level of internal use, and (ii) shocks to exchange rates lead to changes in internal use. We demonstrate that negative shocks to exchange rates lead to decreases in profitability and that negative exchange rate shocks shift downstream innovation away from exploration and towards exploitation, as reflected in reduced patent citations to all science. We assume that this will also reduce internal use of the firm’s own science.

Our instrument uses the yearly change in foreign exchange rates weighted by firm-specific weights. We use two sets of weights: (i) foreign subsidiaries by firm i in each country and (ii) the industry-level export of goods between the US and each foreign country in the main industry of firm i. We include only manufacturing firms (SIC 20-39). The data are for the years 1990-2006, which allows us to include subsidiaries in former USSR countries. The weighted change in exchange rates is computed as:

$$\Delta d_{it} = \sum_c \sum_j S_{ic} \times Export_{jct} \times \Delta d_{tc}$$

Δd_{it} is firm-year change in the weighted-average value of foreign currency relative to the USD. It includes only manufacturing industries and covers the years 1990 to 2006. Higher Δd_{it} indicates the USD becomes stronger indicating a negative shock to USD-denominated profits. S_{ic} is the share of subsidiaries firm i has in country c of all subsidiaries owned by firm i. Subsidiaries information for our sample firm are from the Orbis database, maintained by Bureau VanDyke and is based on the year 2014. $Export_{jct}$ is the share of export by industry j (where firm i operates) to country c in year t. [19]. Δd_{tc} is the change in the USD denominated value of country's c currency between years t and $t-1$. Annual exchange rates are official exchange rates from the World Bank's World Development Indicators. We compute an annual average based on monthly averages (local currency units relative to the U.S. dollar). For countries adopting the Euro currency we manually adjusted Δd_{tc} to zero, for the year of the currency change.

Our sample is conditioned on firm with at least one publication stock. It includes 1901 publishing firms, out of which 1,026 firms have subsidiaries in 52 different countries. The average firm has 54 foreign subsidiaries in 8 different countries. Example of affiliates' countries include: Great Britain (9%), Germany (7%), France (6%), Netherlands (5%), Italy (4%), China (4%), Brazil (3%), India (3%), Russia (1%).

Changes in annual exchange rate vary from a 10th percentile value of -0.09 to 90th percentile value of 0.24 (mean of 0.22 and standard deviation of 1.4).[20] Δd_{it} varies from a 10th percentile value of -0.37 to 90th percentile value of 0.42 (mean of 0.02 and standard deviation of 0.5) for our estimation sample. We compute a dummy variable based on the measure, which receives the value of 1 for devaluation ($\Delta d_{it} > 0$). e lag Δd by two periods as our instrument for one-period lagged internal use.

Table 11 presents the estimation results. We lag Δd by two periods as our instrument for one-period lagged internal use and control for the level of exchange rate, d_{it}[21]. Column 1-4 present the relationship of Δd_{it} with EBIDTA and the use of science – the average number of patent citations to non-patent

[19] Annual industry export flows between US and foreign countries are based on Schott (2010). Data are available for download at: http://faculty.som.yale.edu/peterschott/sub_international.htm

[20] Examples of extreme devaluation include the Brazilian Real that depreciated by more than 1600% during 1993 and 1994, the Indian Rupee depreciated by 30% between 1990-1991, the Chinese Renminbi that depreciated by 50% between 1993-1994 and the British Pound Sterling that depreciated by 50% between 1992-1993.

[21] $d_{it} = \sum_c \sum_j S_{ic} \times Export_{jct} \times d_{tc}$, where d_{tc} is the exchange rate of country's c currency in USD at time t.

literature (NPL), per patent. Consistent with our proposed mechanism, foreign currency devaluation is associated with drop in profits. Based on the estimates from Column 1 and evaluated at the sample average, devaluation is associated with 8% drop in EBIDTA. In other words, exchange rates shocks affect short-term profitability.

Column 2-4 further show foreign currency devaluation is associated with drop in use of science. Column 2 shows that devaluation is associated with reduction of 0.5 citations per patent to the non-patent literature (NPL) which is equivalent to a 9.7% decrease at the mean. Column 3 shows that results hold when restricting the sample to firm-years with patents. Based on the estimates from Column 3, devaluation is associated with 12.5% decrease in average NPL per patent. For Column 4 the dependent variable is share of patents per year with at least one citation to NPL. Evaluated at the sample average, devaluation is associated with 12% drop in share of patents citing NPL. These results are consistent with firms conducting less exploratory inventive activity in leaner times. It is plausible that this would also imply less use of internal science.

Columns 5-7 present the results using devaluation as an instrument for internal use. The first stage estimation instruments internal citations with a dummy variable for $\Delta d_{it} > 0$. As expected, devaluation of foreign currencies is negatively associated with internal use. Based on the estimates from Column 5, devaluation is associated with 8.1% decrease in average internal use (a decrease of 0.65 internal cites based on internal citation sample mean for firms with internal citations. We reject the test for weak instruments with a Kleibergen-Paap F statistic=59 (Staiger and Stock, 1997). Column 7 presents the second stage estimation results, hence, regressing the log of number of publications against the predicted lagged use of science due to profitability shocks. The coefficient estimate on internal citation increases from 0.9 (OLS estimation, Column 6) to 1.4. Based on the coefficient, a 10 percent increase in internal citation is associated with approximately 14% increase in publication per year.

Lastly, Columns 8-10 include both of our instruments, IDD and devaluation, in a single two-stage least-squares specification. The same pattern of results remain in the first and second stage estimations. Using both IVs produces similar estimates of the effect of internal use on publications (1.4 when both IVs are used, as compared to 2 and 1.4 when IDD and devaluation are used separately, respectively). [22]The

[22]The IV procedure returns a higher point estimate, 1.4, for the coefficient on internal citations, as compared to the OLS

Hansen test for overidentifying restrictions is consistent with the instruments being valid; we are unable to reject the null hypothesis that the instruments are uncorrelated with the error term and correctly excluded from the estimated specification (p-value for overidentifying restrictions=0.44, Hansen J statistic=0.59).

Insert Table 11 here

5 Conclusion

Using data on 4,736 publicly traded American firms over the period 1980-2006, this paper studies the relationship between the use of corporate science and investment in research. We systematically match all NPL (non-patent literature) references to publication records from ISI Web of Science to learn about the use of science in research. We make three main contributions. First, we demonstrate that corporate research is useful for invention as it is more likely to be cited by a patent relative to the comparable university publication. Second, we show that internal and external use of science in invention is related to investment in research. Research that is used internally is valuable and firms able to use their research produce more of it. Conversely, research used by rivals reduces value and firms publish less when their research spills over to rivals. Third, we explore determinants of internal use of research. We show how overlap between research and invention teams within the firm explains variation in the use of own science as an input to technology. We study differences in labor market mobility, and in exploratory versus exploitative innovation activity as exogenous factors that affect internal use. We exploit these as sources of exogenous variation to estimate the causal link between internal use and scientific publications by the firm. Our findings advance our understanding of why firms invest in research and the mechanism by which private returns to corporate science are realized. Our findings support the view, as captured by the knowledge production function, that firms invest in research because the scientific knowledge produced is a useful input for the technologies they develop.

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coefficient of 0.9. If the OLS estimates were biased due to unobserved common shocks (such as some firms being more likely to produce technically useful scientific discoveries), one would expect upward biased estimates. IV estimates should therefore produce lower point estimates. If, instead, internal citation is a noisy measure of internal use, IV estimates may produce higher point estimates. Though the samples are somewhat different, making comparisons hazardous, the point estimates reported in Column 11, Table 11 are very similar to the OLS estimates with firm-fixed effects reported in Table 5, Column 4 (for publishing firms).

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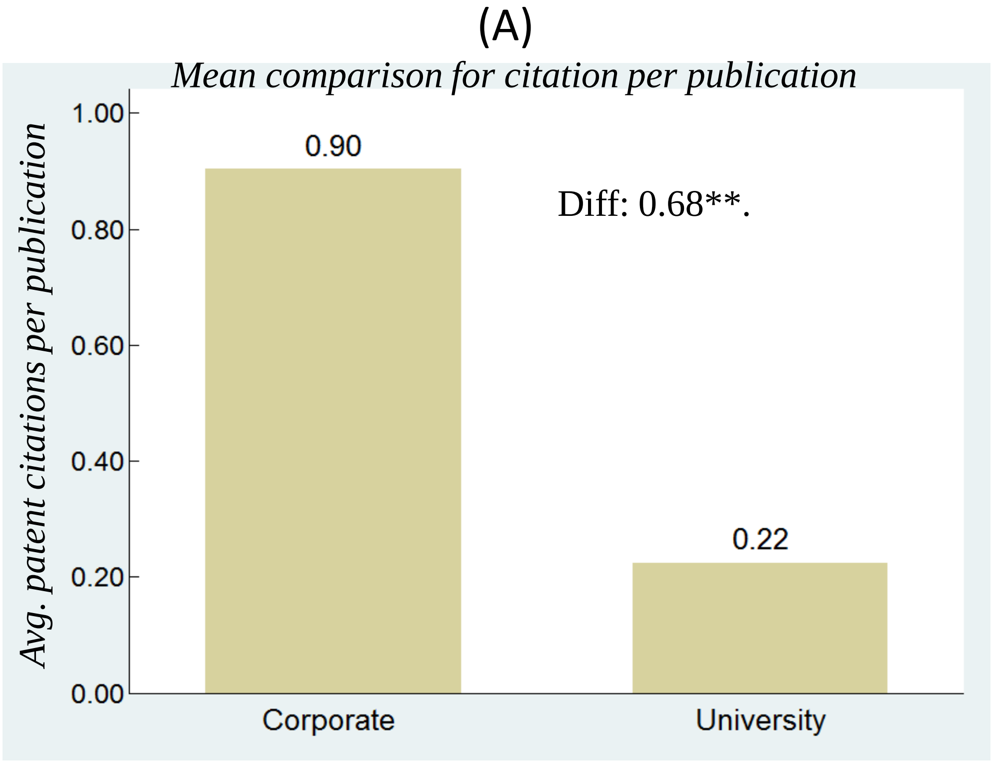
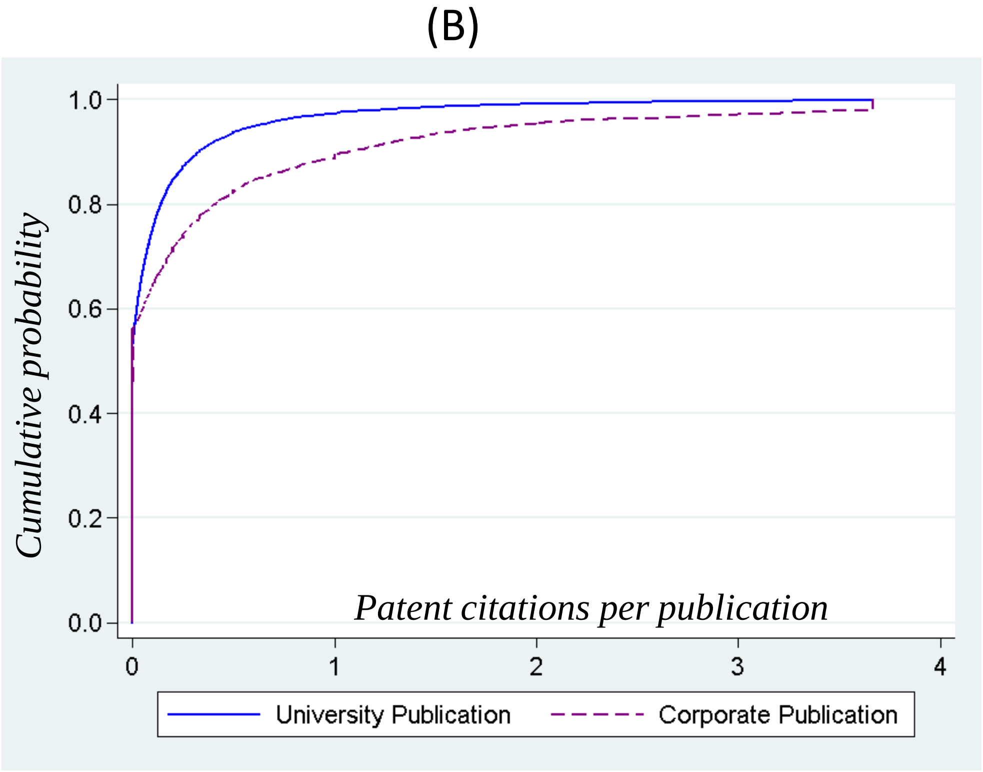
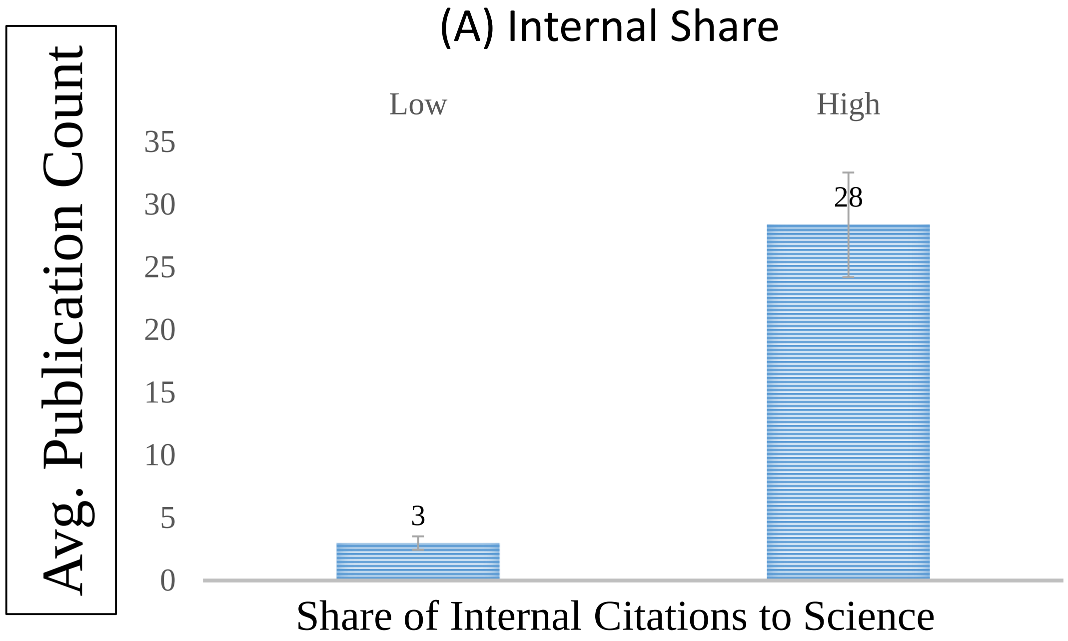
Figure 1. Patent citation to University vs. Corporate Publications, 1980-2006

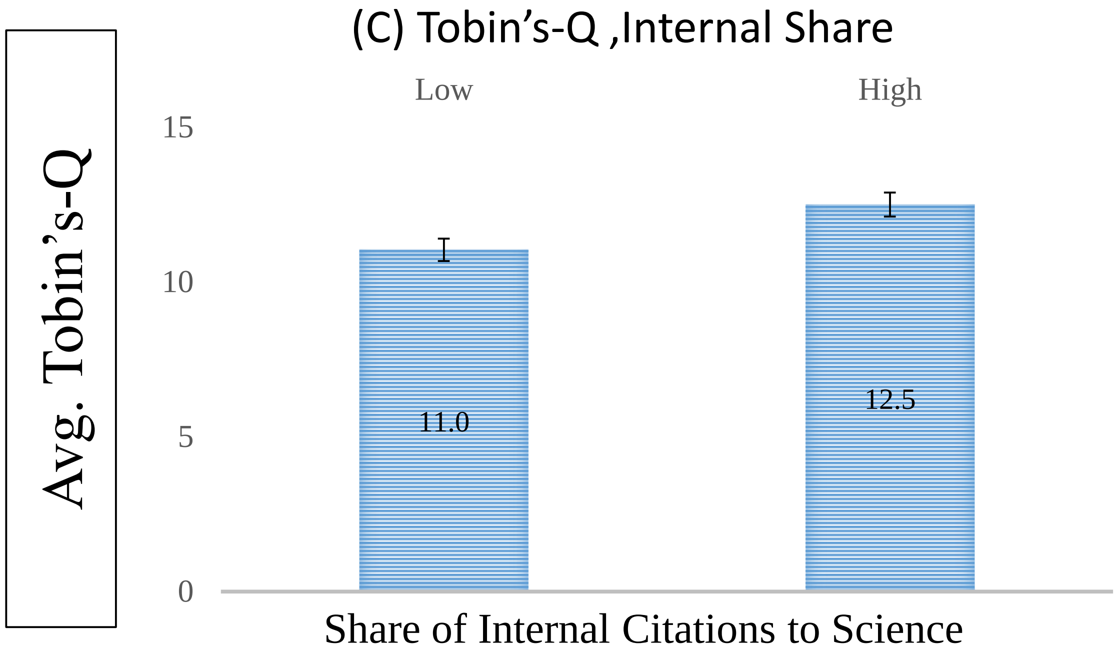


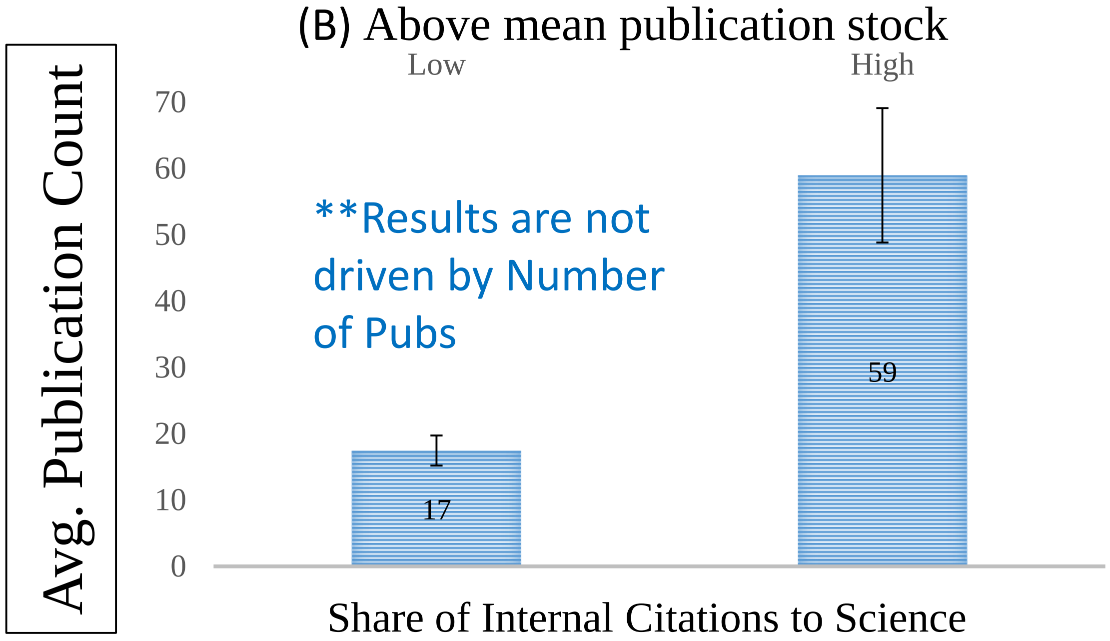


Note: The sample includes publications from the top 100 U.S. universities and corporate publications of our sample firms that were published over the sample period (1980-2006) and covered in Web of Science "Science Citation Index" and "Conference Proceedings Citation Index-Science". Patent citations per publication is measured by total citations (internal and external) per publication by corporate and non-corporate patents granted between 1980 and 2014. Figure A presents mean comparison for university vs. corporate publications by patent citation received per publication. Figure B, plots the cumulative distribution of patent citations received per publication, by corporate and university publications. Number of patent citations per publication is presented with a proximity value in the 99th percentile of the sample.

Figure 2. Mean comparisons for publication count and Tobin's-Q by citation share, 1980-2006







Note: The figures present mean comparisons for average publication count and Tobin's-Q by low and high internal citation share over the sample period (1980-2006). *Share of Internal citations to science* is defined as ratio of self-citations from own patents to internal and external citations received by corporate and non-corporate patents, per year (averaged per firm). *High and low* internal share of citations are defined by above and below the median value of average per firm internal share of citations, respectively. *Average publication count* is defined as publications per firm-year, averaged per firm. Figure 2B restricts the sample to firms with above mean publication stock. *Tobin's Q* is defined as the ratio of market value to assets and is averaged per firm. The sample is conditional on at least one citation to the firm's own science over the sample period.

Figure A1. External and internal citation, matching process

(i) Example of an external citation: the patent owner and cited corporate publication are different

(12) **United States Patent** (10) **Patent No.:** **US 6,468,596 B1**
Liu et al. (45) **Date of Patent:** **Oct. 22, 2002**

(54) **LASER-ASSISTED IN-SITU FRACTIONATED LUBRICANT AND A NEW PROCESS FOR SURFACE OF MAGNETIC RECORDING MEDIA**

(75) Inventors: **Youming Liu**, Palo Alto; **Jialuo Jack Xuan**, Milpitas; **Xiaohua Shel Yang**, Fremont; **Chung-Yuang Shih**, Cupertino; **Vidya K. Gubbi**, Milpitas, all of CA (US)

(73) Assignee: **Seagate Technology LLC**, Scotts Valley, CA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **09/577,674**

(22) Filed: **May 25, 2000**

Related U.S. Application Data

(60) Provisional application No. 60/144,357, filed on Jul. 15, 1999.

(51) **Int. Cl.**[7] **C08F 2/48**; C08J 7/18; C23C 14/30

(52) **U.S. Cl.** **427/508**; 427/554; 427/596

(58) **Field of Search** 427/510, 554, 427/555, 556, 597, 127, 226, 258, 261, 264, 270, 271, 402, 508

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Primary Examiner—Shrive P. Beck
Assistant Examiner—Eric B. Fuller
(74) *Attorney, Agent, or Firm*—McDermott, Will & Emery

(57) **ABSTRACT**

A magnetic recording medium is formed with enhanced tribological performance by applying a raw, unfractionated lubricant having a wide molecular weight distribution over a disk surface and treating the deposited lubricant with a laser light beam to effect in-situ fractionation of the lubricant to a very narrow molecular weight distribution. Embodiments of the present invention also include laser treating a deposited lubricant to increase the thickness of the bonded lube layer.

(ii) Example of an internal citation: the patent owner and cited corporate publication are the same

(12) **United States Patent** (10) **Patent No.:** **US 7,193,323 B2**
Cabral, Jr. et al. (45) **Date of Patent:** **Mar. 20, 2007**

(54) **ELECTROPLATED COWP COMPOSITE STRUCTURES AS COPPER BARRIER LAYERS**

(75) Inventors: **Cyril Cabral, Jr.**, Ossining, NY (US); **Stefanie R. Chiras**, Peekskill, NY (US); **Emanuel Cooper**, Scarsdale, NY (US); **Hariklia Deligianni**, Tenafly, NY (US); **Andrew J. Kellock**, Sunnyvale, CA (US); **Judith M. Rubino**, Ossining, NY (US); **Roger Y. Tsai**, Yorkstown Heights, NY (US)

(73) Assignee: **International Business Machines Corporation**, Armonk, NY (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **10/714,966**

(22) Filed: **Nov. 18, 2003**

(65) **Prior Publication Data**

US 2005/0104216 A1 May 19, 2005

(51) **Int. Cl.**
H01L 23/48 (2006.01)
H01L 23/52 (2006.01)

(52) **U.S. Cl.** **257/751**; 257/752; 257/762

(58) **Field of Classification Search** 257/751–753, 257/758, 759, 761–763

See application file for complete search history.

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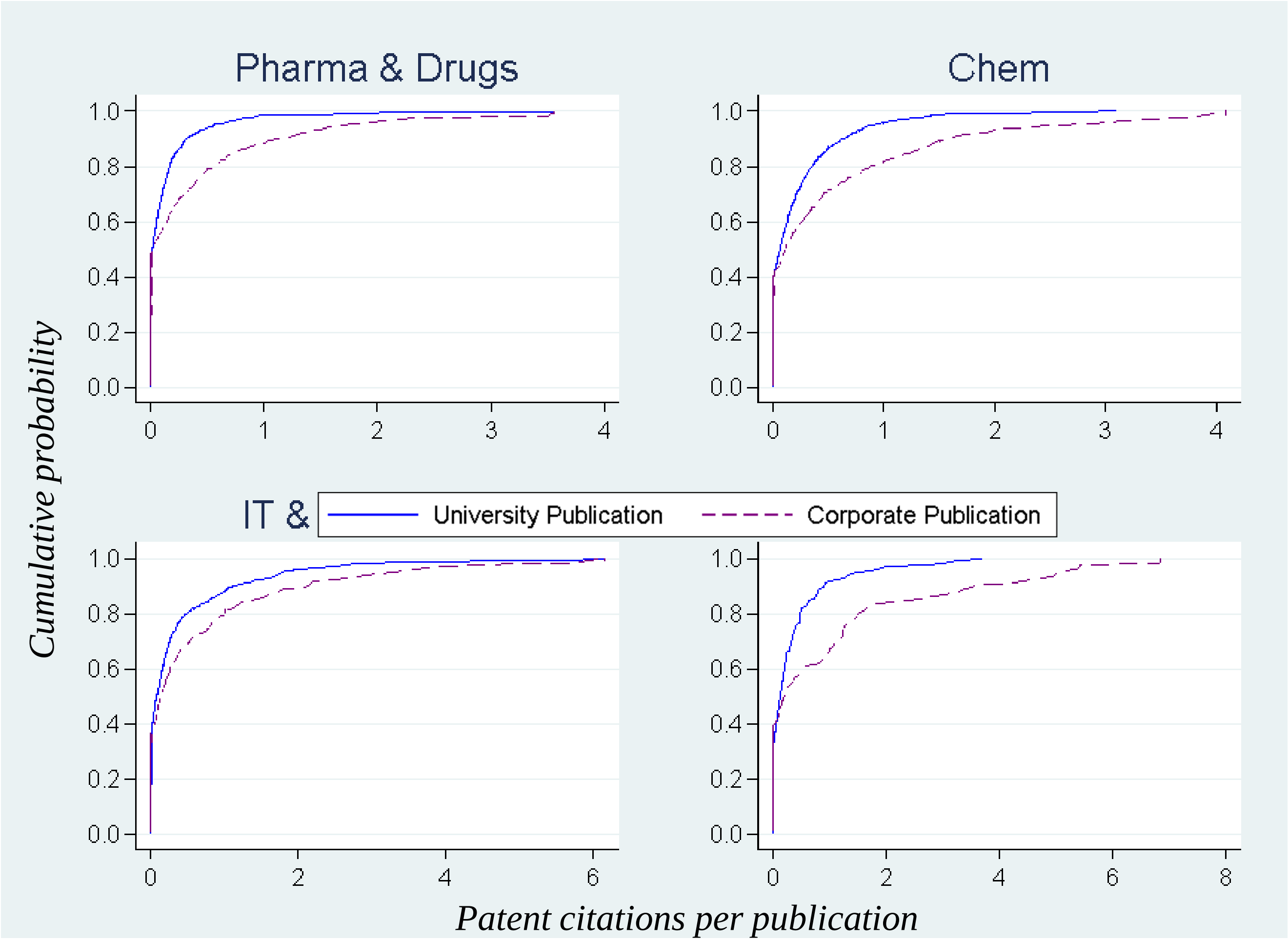
Primary Examiner—Hung Vu
(74) *Attorney, Agent, or Firm*—Connolly Bove Lodge & Hutz, LLP; Robert M. Trepp

(57) **ABSTRACT**

A composite material comprising a layer containing copper, and an electrodeposited CoWP film on the copper layer. The CoWP film contains from 11 atom percent to 25 atom percent phosphorus and has a thickness from 5 nm to 200 nm. The invention is also directed to a method of making an interconnect structure comprising: providing a trench or via within a dielectric material, and a conducting metal containing copper within the trench or the via; and forming a CoWP film by electrodeposition on the copper layer. The CoWP film contains from 10 atom percent to 25 atom percent phosphorus and has a thickness from 5 nm to 200 nm. The invention is also directed to a interconnect structure comprising a dielectric layer in contact with a metal layer; an electrodeposited CoWP film on the metal layer, and a copper layer on the CoWP film.

18 Claims, 6 Drawing Sheets

Figure A2. Cumulative Probability of being cited -University vs. Corporate Publications, by Industry, 1980-2006



Note: The sample includes publications from the top 100 U.S. universities and corporate publications of our sample firms that were published over the sample period (1980-2006) and covered in Web of Science "Science Citation Index" and "Conference Proceedings Citation Index-Science". *Patent citations per publication* is measured by total citations (internal and external) per publication by corporate and non-corporate patents granted between 1980 and 2014. The figure plots the cumulative distribution of patent citations received per publication, by corporate and university publications. Number of patent citations per publication is presented with a proximity value in the 99^{th} percentile of the sample. Industry classification is based on the journal's subject category.

Table 1. Summary Statistics for Main Variables

VARIABLE	# Obs.	# Firms	Mean	Std. Dev.	Distribution 10th	50th	90th
Publications count	32,923	2,413	9	51	0	0	9
Publications stock	32,923	2,413	104	762	0	2	75
Patents stock	42,111	4,274	89	441	1	6	126
Patents count	42,111	4,274	16	87	0	1	24
R&D expenditures($mm)	57,765	4,736	55	319	0.25	5	67
R&D stock($mm)	57,765	4,736	231	1,467	0.5	17	260
Market value ($mm)	57,765	4,736	2,606	16,111	8	151	3,229
Tobin's Q (Market value/Assets)	57,765	4,736	3.9	5	1	2	11
Sales ($mm)	57,765	4,736	1,394	8,063	2	66	1,997
Assets ($mm)	57,765	4,736	1,474	8,003	7	80	2,189
Inventor-author overlap	16,538	2,081	0.2	0.3	0	0	0.9

Notes: This table provides summary statistics for the main variables used in the econometric analysis. The sample is at the firm-year level and includes an unbalanced panel of 4,736 US HQ publicly traded companies (out of which 2,413 are publishing companies) over the sample period, 1980-2006. These firms have at least one year with positive R&D expenditures and at least one patent during the sample period. The sample for all publication variables is restricted to publishing firms. Inventor-author overlap is the share of non-collaborative patents per firm-year where the inventor team includes at least one author of a corporate publication published by the firm up to 3 years prior to the patent's grant year. For Inventor-author overlap, the sample is conditional on at least one publication stock and on firm-years with granted non-collaborative patents.

Table 2. Summary Statistics for Citations Variables (only publishing firms)

VARIABLE	(1) Number of firms with positive values	(2) Average value per firm-year	(3) Number of citing patents per firm-year	(4) Number of cited publications per firm-year
Patent citations to own publications	799	23	18	14
Internal patent citations to own publications	388	8	5.5	5.8
External patent citations to own publications	760	21	17	13

Notes: This table provides summary statistics for the main citation variables used in the econometric analysis. The sample is at the firm-year level and is conditional on publishing firms.

Table 3. High Internal Use *vs.* Low Internal Use (only publishing firms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		High Share of internal citations			Low Share of internal citations		
VARIABLE	(3) minus (6)	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Publications flow/R&D expenditures	0.2**	241	0.4	0.6	2,172	0.2	0.4
Patents stock/R&D expenditures	0.1*	241	0.6	0.7	2,172	0.5	0.7
R&D expenditures/Sales	0.1**	241	0.2	0.1	2,172	0.1	0.1
Inventor-author overlap	0.3**	241	0.5	0.3	2,172	0.2	0.3

Notes: This table presents mean comparison tests for firms with high Share of internal citations *vs.* firms with low Share of internal citations. Share of Internal citations to science is defined as ratio of self-citations from own patents to internal and external citations received by corporate and non-corporate patents, per year (averaged per firm). High and low internal share of citations are defined by above and below the mean value of average per firm internal share of citations, respectively. * and ** denote that the difference in means is significant at the 5% and 1% level, respectively. The unit of analysis is a firm. Values are averaged over the period 1980-2006.

Table 4. Likelihood of a Patent Citation: Corporate *vs.* University Publications

	Dependent variable: *Dummy for a citation by a patent*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Quality control	Journal FE	Top 10 universities	Journal-issue FE	Excl. Internal citations	High quality patents	Industry variation
Dummy for corporate publication	0.110	0.127	0.069	0.062	0.069	0.055	0.047	0.060
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(1+Citations by scientific publications)		0.052	0.052	0.071	0.054	0.051	0.035	0.052
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dummy for corporate publication ×:								
Dummy For IT & Computers & Telecom								0.019
								(0.003)
Dummy For Pharma & Drugs								0.021
								(0.003)
Dummy For Biotech								0.073
								(0.008)
Dummy For Energy								-0.013
								(0.004)
Dummy For Chemistry								0.033
								(0.003)
Publication year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Journal fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample share of corporate publication	0.23	0.23	0.23	0.59	0.23	0.23	0.23	0.23
Observations	1,269,992	1,269,992	1,269,992	496,279	1,269,992	1,269,992	1,269,992	1,269,992
R-squared	0.03	0.09	0.19	0.22	0.38	0.18	0.14	0.19

Notes: This table presents the estimation results of a Linear Probability Model of the probability that a publication is ever cited by a patent for publications by corporations and by universities. The sample includes all publications of our sample firms and all publications by top100 research universities, published over the sample period (1980-2006) and covered in Web of Science "Science Citation Index" and "Conference Proceedings Citation Index-Science". Patent citations are by patents granted between 1980 and 2014. The unit of observation is the publication. Corporate publication dummy is equal to one for articles with at least one author employed by our sample of Compustat firms. The dependent variable, dummy for citation by a patent, is equal to one if a publication has at least one patent citation. Column 4 restricts the samples to university publications from top 10 U.S. universities based on ShanghaiRanking's. Column 6 excludes self-citation of patents to own publications. High quality patents (Column 7) includes all patents with above median citations compared to their grant year cohort. Industry classification (Column 8) is based on the journal's subject category. Robust standard errors in parentheses.

Table 5. Internal Use and Publication Output

Dependent variable: ln(1+number of publications)					
	(1)	(2)	(3)	(4)	(5)
	Pooled	Between-firms	Within-firms	Publishing firms only	Share internal citations
ln(1+Internal patent cites to own publications)$_{t-1}$	10.378	15.820	1.555	1.412	
	(0.759)	(2.120)	(0.200)	(0.194)	
Share of internal citations$_{t-1}$ (Internal cites/NPL)					0.099
					(0.035)
ln(R&D stock)$_{t-1}$	0.095	0.103	0.065	0.097	0.066
	(0.007)	(0.007)	(0.004)	(0.006)	(0.004)
ln(1+Patent stock)$_{t-1}$	0.152	0.179	0.076	0.088	0.079
	(0.012)	(0.010)	(0.005)	(0.007)	(0.005)
ln(Sales)$_{t-1}$	0.028	0.001	0.047	0.088	0.047
	(0.005)	(0.001)	(0.003)	(0.005)	(0.003)
Firm fixed-effects	No	No	Yes	Yes	Yes
Industry dummies (4 digit)	Yes	Yes	-	-	-
Year dummies	Yes	No	Yes	Yes	Yes
Sample Avg. - Publication count	5.2	2.9	5.2	9.1	5.2
Number of firms	4,634	4,634	4,634	2,380	4,634
Observations	53,029	4,634	53,029	30,510	53,029
R-squared	0.63	0.59	0.87	0.85	0.87

Notes: This table presents OLS estimation results for the relationship between past patent citations to own publications and future annual publications, for the period 1980-2006. Internal cites to own publications include patent citations up to year t-1 to publications published up to the same year. All specifications include a dummy variable that receives the value of one for firms that never published up to the focal year. Internal citation variable is divided by 100 and presented in log value. Column 2 averages variables at the firm level and performs a cross section analysis. In Columns 5-6 the sample is conditional on firms with below and above median average sales, respectively. Standard errors (in brackets) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by firms.

Table 6. Knowledge Spillovers: External Citations and Publication Output

Dependent variable: ln(1+Number of publications)			
	(1)	(2)	(3)
	External citations	Citations received, by Segment and TECH	Publishing firms only
ln(1+Internal patent cites to own publications)$_{t-1}$	1.876	1.696	1.472
	(0.247)	(0.226)	(0.217)
ln(1+External patent cites to own publications)$_{t-1}$	-0.128		
	(0.052)		
ln(1+External patent cites to own publications, Segment)$_{t-1}$		-0.995	-1.208
		(0.259)	(0.246)
ln(1+External patent cites to own publications, TECH)$_{t-1}$		0.217	0.344
		(0.125)	(0.121)
ln(R&D stock)$_{t-1}$	0.065	0.065	0.097
	(0.004)	(0.004)	(0.006)
ln(1+Patent stock)$_{t-1}$	0.076	0.077	0.090
	(0.005)	(0.005)	(0.007)
ln(Sales)$_{t-1}$	0.047	0.047	0.088
	(0.003)	(0.003)	(0.005)
Firm fixed-effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Sample Avg. - Publication count	5.2	5.2	9.1
Number of firms	4,634	4,634	2,380
Observations	53,029	53,029	30,510
R-squared	0.87	0.87	0.85

Notes: This table presents OLS estimation results for the relationship between external citations and publications. External cites to own publications include corporate and non-corporate patent citations. Segment and TECH measure the product market proximity and the technology market proximity, respectively. All specifications include dummy variable that receives the value of one for firms that never published up to the focal year. All citation variables are divided by 100 and presented in log value. Standard errors (in brackets) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by firms.

Table 7. Patents and Use of Internal Research

	(1)	(2)	(3)	(4)
Dependent variable: ln(1+Number of citation-weighted patents)				
	Baseline	Within firms	Interaction Within firms	Only publishing firms
Share of internal citations$_{t-1}$	0.398	0.198	-0.603	-0.509
	(0.100)	(0.047)	(0.168)	(0.155)
ln(R&D stock)$_{t-1}$ × Share of internal citations$_{t-1}$			0.154	0.131
			(0.031)	(0.029)
ln(R&D stock)$_{t-1}$	0.208	0.166	0.165	0.256
	(0.009)	(0.006)	(0.006)	(0.013)
ln(1+Publication stock)$_{t-1}$	0.196	0.137	0.135	0.135
	(0.014)	(0.008)	(0.008)	(0.013)
Firm fixed-effects	-	Yes	Yes	Yes
Industry dummies (4 digit)	Yes	No	No	No
Year dummies	Yes	Yes	Yes	Yes
Number of firms	4,634	4,634	4,634	2,259
Observations	53,029	53,029	53,029	23,466
R-squared	0.71	0.86	0.86	0.87

Notes: This table presents results OLS estimation results of a patent equation, for the period 1980-2006. Patents are weighted by citations. Share of internal citations is defined as ratio of citations the firm's publications receive from own patents to citations received from all patents. All specifications include a dummy variable that receives the value of one for firm-years without patents and a dummy variable that receives the value of one for firm-years without citations. Standard errors (in brackets) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by firms.

Table 8. Stock Market Value And Internal Use

Dependent variable: ln(Tobin's Q)	(1)	(2)	(3)	(4)	(5)
	Pooled	Within-firms	External citations	Publishing firms only	Citations to external publications by Segment and TECH
Cumulative internal patent cites to own publications/Assets$_{it-1}$	1.648	2.381	1.769	1.481	2.166
	(0.357)	(0.486)	(0.584)	(0.575)	(0.495)
Cumulative external patent cites to own publications/Assets$_{it-1}$			0.305	0.195	
			(0.151)	(0.152)	
Cumulative external patent cites to own publications, Segment/Assetsi$_{t-1}$					-0.558
					(0.213)
Cumulative external patent cites to own publications, TECH/Assets$_{it-1}$					0.383
					(0.133)
R&D Stock/Assets$_{it-1}$	0.149	0.143	0.142	0.136	0.142
	(0.003)	(0.005)	(0.005)	(0.007)	(0.005)
Patents Stock/Assets$_{it-1}$	0.046	-0.002	-0.005	0.000	-0.004
	(0.007)	(0.010)	(0.011)	(0.013)	(0.011)
Firm fixed-effects	-	Yes	Yes	Yes	Yes
Industry dummies (4 digit)	Yes	No	No	No	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Sample Avg. - Tobin's Q	3.8	3.8	3.8	3.9	3.8
Number of firms	3,418	3,418	3,418	1,790	3,418
Observations	30,308	30,308	30,308	15,857	30,308
R-squared	0.41	0.67	0.67	0.70	0.67

Notes: This table presents OLS estimation results for the relationship between citations to firm's own publications and Tobin's-Q, for the period 1980-2006. Tobin's-Q is defined as the ratio of market value to assets. Internal and external patent citations are lagged by 1 year and presented in stock value divided by assets. External citation include corporate and non-corporate patent citations. Segment and TECH measure the product market proximity and the technology market proximity, respectively. Standard errors (in brackets) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by

Table 9. Research-Invention Overlap And Internal Use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unit of analysis:	Firm-year						Patent
Dependent variable:	Dummy for internal citation		Dummy for external-citation	Internal Citation Share		Internal Citation Share - Lag 5	Dummy for self-citing patent
Inventor-author overlap$_{t-1}$	0.118	0.055	-0.036	0.054	0.038	0.047	
	(0.013)	(0.013)	(0.016)	(0.006)	(0.007)	(0.007)	
Overlap patent-level dummy							0.027
							(0.003)
ln(R&D stock)$_{t-1}$	0.003	0.012	0.002	-0.002	-0.002	0.004	0.005
	(0.004)	(0.007)	(0.010)	(0.002)	(0.003)	(0.003)	(0.003)
ln(1+Patent stock)$_{t-1}$	0.027	0.030	0.028	0.009	0.009	0.013	-0.001
	(0.004)	(0.007)	(0.007)	(0.002)	(0.003)	(0.003)	(0.001)
ln(1+Publication stock)$_{t-1}$	0.071	0.081	0.156	-0.009	-0.002	0.021	0.007
	(0.004)	(0.009)	(0.009)	(0.002)	(0.004)	(0.004)	(0.002)
ln(Sales)$_{t-1}$	-0.004	0.010	-0.007	-0.003	0.006	0.003	0.000
	(0.003)	(0.006)	(0.007)	(0.002)	(0.004)	(0.004)	(0.002)
Firm fixed-effects	No	Yes	Yes	No	Yes	Yes	Yes
Industry dummies	Yes	-	-	Yes	-	-	-
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPC 4-digit dummies	-	-	-	-	-	-	Yes
Dep. Var. sample average:	0.118	0.118	0.256	0.047	0.047	0.043	0.015
Number of firms	2,052	2,052	2,052	2,052	2,052	2,052	4,013
Observations	15,987	15,987	15,987	15,987	15,987	15,987	661,898
R-squared	0.38	0.56	0.63	0.25	0.42	0.32	0.08

Notes: This table presents OLS estimation results for the relationship between author-inventor overlap and internal and external citation to science. Columns 1-6 are at the firm-year level. Dummy for internal (external) citation is equal to one if the firm receives at least 1 internal (external) citation at the focal year to any of its publication published up to the focal year. Internal citations share is defined as ratio of self-citations from own patents to internal and external citations received by all patents (corporate and non-corporate patents). Inventor-author overlap is measured by the share of non-collaborative patents per firm-year where the inventor team includes at least one author of a corporate publication published by the firm up to 3 years prior to the patent's grant year. Column 6 includes only citations to publications up to five years old. The sample is conditional on at least one publication stock and on firm-years with patents. Column 7 is at the patent level and is restricted to all non-collaborative patents of our sample firms granted between 1980 and 2006. Dummy for self-citing patent, equals one for patents that self-cite corporate science. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms.

Table 10. Instrumental Variable Estimation I: Inevitable Disclosure Doctrine and Publication Output (Sample: Publishing Firms)

	(1)	(2)	(3)
Dependent variable:	$\ln(1+\text{Internal cites})_{t-1}$	$\ln(1+\text{Number of publications})$	
	First Stage	OLS	2SLS
$\ln(\text{Internal cites to own publications})_{t-1}$		1.074	2.001
		(0.049)	(0.610)
Inevitable disclosure doctrine dummy $_{t-2}$	0.022		
	(0.005)		
$\ln(\text{R\&D stock})_{t-1}$	0.044	0.260	0.219
	(0.002)	(0.019)	(0.027)
$\ln(\text{Patent stock})_{t-1}$	0.050	0.085	0.038
	(0.002)	(0.015)	(0.031)
$\ln(\text{Sales})_{t-1}$	-0.013	-0.007	0.004
	(0.001)	(0.010)	(0.009)
$\ln(\text{Total employment at state level})_{t-1}$	0.010	0.040	0.032
	(0.003)	(0.021)	(0.010)
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Weak identification(Kleibergen-Paap)	F=20.97		
Sample Avg. - Publication count	11	11	11
Number of firms	2,197	2,197	2,197
Observations	21,146	21,146	21,146
R-squared	0.22	0.53	0.47

Notes: This table presents Two-Stage Least Squares estimation results for the effect of patent citations to own publications on the number of future publications, for the period 1985-2006. The endogenous variable, internal cites to own publications, is instrumented by the Inevitable Disclosure Doctrine (IDD) status at the state-year level. For the IV estimation, internal citations only include citations to publications published no earlier than five years prior to the citing patent and the sample is conditioned on at least one publication stock. The IDD dummy is equal to one if the Inevitable Disclosure Doctrine was in effect at the state level two years prior to the focal year. Total employment at state level is based on U.S. Bureau of Economic Analysis (BEA). Standard errors (in brackets) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by firms.

Table 11. Instrumental Variable Estimation II: Changes in Foreign Exchange Rates (Sample: Publishing Firms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS				IV: Devaluation			IVs: IDD and devaluation		
Dependent variable:	Profits (EBIDTA)	Avg. NPL citations per patent		Share of patents with NPL>0	ln(1+Internal cites)$_{t-1}$	ln(1+Number of publications)		ln(1+Internal cites)$_{t-1}$	ln(1+Number of publications)	
	Publishing firms	Publishing firms	Exc. zero patents	Publishing firms	First Stage	OLS	IV	First Stage	OLS	IV
ln(Internal cites to own publications)$_{t-1}$						0.886	1.408		0.885	1.434
						(0.040)	(0.232)		(0.041)	(0.223)
Devaluation dummy$_{t-2}$	-33.266	-0.097	-0.125	-0.044	-0.081			-0.079		
	(11.577)	(0.031)	(0.043)	(0.010)	(0.010)			(0.011)		
Inevitable disclosure doctrine dummy$_{t-2}$								0.023		
								(0.008)		
ln(R&D stock)$_{t-1}$					0.068	0.244	0.209	0.067	0.241	0.205
					(0.003)	(0.019)	(0.017)	(0.003)	(0.019)	(0.016)
ln(Patent stock)$_{t-1}$					0.093	0.066	0.019	0.093	0.067	0.017
					(0.004)	(0.016)	(0.022)	(0.004)	(0.016)	(0.021)
ln(Assets)$_{t-1}$	88.434	-0.074	-0.100	-0.028	-0.020	-0.006	0.006	-0.019	-0.004	0.007
	(9.969)	(0.007)	(0.009)	(0.002)	(0.002)	(0.010)	(0.007)	(0.002)	(0.010)	(0.006)
Exchange rate level$_t$					-0.001	0.001	0.001	-0.001	0.001	0.001
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(Total employment)$_{t-1}$								0.020	0.031	0.021
								(0.004)	(0.021)	(0.010)
Firm fixed-effects	Yes	No	No	No	No	No	No	No	No	No
Industry dummies	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weak identification(Kleibergen-Paap)					F= 59			F=29.168 > Stock-Yogo CV 5%= 13.46		
Overidentification (Hansen test)								t-statistic=0.59		
Dependent variable sample average:	403	5	7	0.36	0.83	11	11	0.83	11	11
Number of firms	1901	1901	1751	1901	1901	1901	1901	1901	1901	1901
Observations	14,565	14,565	10,883	14,565	14,565	14,565	14,565	14,565	14,565	14,565
R-squared	0.91	0.32	0.10	0.39	0.28	0.54	0.50	0.28	0.54	0.50

Notes: This table presents instrumental variable estimation results for the effect of patent citations to own science on firm's future publication, for the period 1990-2006. The sample includes firms with at least one publication stock, out of which 1,007 firms have foreign subsidiaries. The endogenous variable, internal citation in year t-1, is instrumented at the firm-year level by a devaluation dummy that is based on weighted changes in exchange rates in countries where the firm has subsidiaries. Profit is measured by EBIDTA. NPL citations are cites in year t by the focal firm's patents to any Web of Science article. Standard errors (in brackets) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by firms.

Table A1. Main Variables Definition

Variable	Description	Data Source
Publications count	Publication count for firm i in year t, including all publications with at least one author employed by the focal firm.	Web of Science articles, covered in "Science Citation Index" and "Conference Proceedings Citation Index-Science", 1980-2006
Publication stock	Publication stock in year t for firm i is calculated by: $Publication\_stock_t = Pub_t + Publications\_stock_{t-1}$, where Pub_t is the focal firm's publication count in year t.	Web of Science
Patent count	Patent count in year t for firm i	NBER 2006 patent data project
Patent Stock	Patent stock in year t for firm i is calculated by: $Patent\_stock_t = Patent_t + Patent\_stock_{t-1}$, where $Patent_t$ is the focal firm's patent count in year t.	NBER 2006 patent data project
Internal citations to firm’s own publications	Annual flow of internal patent citations to firm's i publications	PatStat database and citation match for patents granted at the focal year and publications published from 1980 until the focal year.
External citations to firm’s own publications	Annual flow of external patent citations to firm's i publications. Includes citations by corporate and non-corporate patents.	PatStat database and citation match for patents granted at the focal year and publications published from 1980 until the focal year.
External citations to firm's own publications, Segmen	Annual flow of external patent citations to firm's i publications, weighted by product market proximity of the citing and cited firms. Product market proximity is computed based on each firm's sales share distribution across line of business listed within the Compustat operating segments database.	Compustat operating segments database, PatStat database and citation match for patents granted at the focal year and publications published from 1980 until the focal year.
External citations to firm's own publications, TECH	Annual flow of external patent citations to firm's i publications, weighted by technology market proximity of the citing and cited firms. Technology market proximity is computed based on each firm’s patent share distribution across different technology fields.	PatStat database and citation match for patents granted at the focal year and publications published from 1980 until the focal year.
Share of internal citations	Share of internal citations to science is defined as ratio of self-citations from own patents to internal and external citations received by corporate and non-corporate patents, per year.	PatStat database and citation match for patents granted at the focal year and publications published from 1980 until the focal year.
Inventor-author overlap	The share of patents per firm-year, for which the inventor team includes at least one author of a corporate publication published by the firm up to 3 years prior to the patent’s grant year.	Web of Science, NBER 2006, HBS Patent Inventor Database. Including all non-collaborative patents and publications related to our sample firms during the sample period (1980-2006),
Market value	Following Griliches (1981), market value per firm-year is defined as the sum of the values of common stock, preferred stock, and total debt net of current assets. *Tobin’s-Q* is defined as the ratio of market value to assets.	U.S. Compustat
R&D stock	R&D stock per firm-year is calculated using a perpetual inventory method with a 15 percent depreciation rate (Hall et al., 2005), such that the R&D stock, GRD, in year t is $GRD_t = R_t + (1-\delta)GRD_{t-1}$ where R_t is the focal firm's R&D expenditure in year t based on Compustat data and $\delta = 0.15$.	U.S. Compustat
Assets	The book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles other than R&D.	U.S. Compustat

Table A2. SIC Classification by Main Industries

Category	Description	Related 4-digit sic codes in our sample of firms
Telecommunication	Telecom, Communication- sys., equip., services	3661 3663 3669 4812 4813 4822 4832 4833 4841 4899
IT & Software	Dvlp/Pvd/Sale - IT, IT services, software	5040 5045 5734 7370 7371 7372 7373 7374
Machinery/equipment/system	Mnfr/sale/rent - Machinery, Systems, Equipment, Instruments, Components, Tools not elsewhere included (e.g, med, lab, heating, transportation, construction, measurement, electrical)	3420 3430 3433 3510 3523 3524 3530 3531 3532 3533 3537 3540 3541 3550 3555 3559 3560 3561 3562 3564 3567 3569 3580 3585 3590 3711 3713 3714 3715 3716 3720 3728 3743 3760 3790 3821 3822 3823 3824 3825 3826 3827 3829 3841 3842 3843 3844 3845 5047 5070 5080 5082 5084 7350 7359
Energy	Electricity, Oil, Gas, Power station- including: utility, exploration, equip, services, machinery, tools, etc.	1311 1381 1382 1389 1600 1623 1700 1731 2911 2990 4911 4922 4923 4924 4931 4932 5171 5172
Chemicals	Chemicals- Mnfr&Sale	1000 1040 1044 1090 1220 1221 2800 2810 2821 2851 2860 2870 2890 2891 3320 3330 3334 3341 3350 3357 3360 3390 5160
Electronics & Semiconductor	Mnfr&Sale/rent-electronic products and equipments including components; semiconductor; computers including system and components.	3570 3571 3572 3575 3576 3577 3578 3579 3600 3612 3613 3620 3621 3630 3634 3640 3651 3670 3672 3674 3677 3678 3679 3690 3695 3812 3861 3873 5063 5064 5065 5700 5731 7377
Drugs, Pharmaceuticals and Biotechnology	Drugs, pharmaceuticals & biotech- Mnfr, Sale & Services	2833 2834 2835 2836 5122 5912 8731

Table A3. Publications and Citations to Science by Industry, 1980-2006

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	ln(1+No. of Publications)						
	Electr&Semicond	Pharma&Biotech	Chemicals	Energy	IT & Sftwr	Telecom	Mach&Eqpt
ln(*Internal patent cites to own science*) $_{t-1}$	2.068	-0.242	-0.773	3.287	2.605	0.448	5.637
	(0.656)	(0.318)	(2.831)	(1.304)	(0.818)	(0.148)	(1.469)
ln(*External patent cites to own science*) $_{t-1}$	-0.431	0.481	-0.827	-1.657	-0.937	-0.248	-1.736
	(0.153)	(0.086)	(0.344)	(0.287)	(0.226)	(0.058)	(0.331)
ln(*R&D stock*) $_{t-1}$	0.083	0.196	0.163	-0.016	0.033	0.060	0.039
	(0.010)	(0.015)	(0.020)	(0.039)	(0.011)	(0.012)	(0.009)
ln(*Patent stock*) $_{t-1}$	0.090	0.117	0.041	0.095	0.076	0.092	0.079
	(0.009)	(0.012)	(0.020)	(0.042)	(0.015)	(0.013)	(0.007)
ln(*Sales*) $_{t-1}$	0.035	0.071	0.081	0.013	0.044	-0.004	0.055
	(0.007)	(0.010)	(0.018)	(0.016)	(0.007)	(0.007)	(0.006)
Firm fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.86	0.88	0.85	0.94	0.86	0.94	0.82
Observations	9,745	6,246	2,447	1,065	4,978	3,122	13,084

Notes: This table presents OLS estimation results for the relationship between internal and external citations to firm's own science and production of publications, by industry. Industry classification is based on four-digit main SIC code. Publication count is per year t. Patent citation count variables are lagged by 1 year and include citations to publications that were published up to that year. External cites to own publications include corporate and non-corporate patent citations. All citations variables are divided by 100 and presented in log value. All specifications include dummy variable that receives the value of one for firms that never published up to the focal year. Standard errors (in brackets) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by firms.