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How Does Basic Research Improve Innovation Performance in the World's Major Pharmaceutical Firms?

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How Does Basic Research Improve Innovation Performance in the World's Major Pharmaceutical Firms?

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Abstract

Employing a panel (1995-2015) of large R&D spending pharmaceutical firms, we investigate how internal basic research increases a firm's innovative performance. We disentangle two mechanisms through which internal basic research affects technology development: (1) as strengthening of the firm's absorptive capacity to build on externally conducted science, and (2) as a direct source of the firm's innovation. We find that the positive relationship between internal basic research and innovation performance is significantly mediated by these two mechanisms, with the absorptive capacity mechanism relatively more important. The mediation relationships are more pronounced in recent years, with basic research as a direct source of innovation increasing in importance. This pattern is associated with a decline of corporate investments in basic research over time, and suggests that firms have adopted a more judicious and targeted approach to basic research aimed at getting more leverage out of a smaller commitment to basic research.

JEL classification: O31, O32.

Introduction

There is abundant evidence of the important role of basic research in driving innovation, economic growth and welfare (Mansfield, 1980; Jaffe, 1989; Griliches, 1986; Adams, 1990; Salter and Martin, 2001; Toole, 2012). Basic research can be defined as activities that are directed towards the general advancement of knowledge about the physical world without specific commercial objectives (Nelson, 1959). These activities expand the knowledge base available for firms to draw upon in their technology development activities (Klevorick *et al.*, 1995). The fact that basic research addresses fundamental questions that do not aim to solve narrowly defined practical problems has led to its characterization as an act of 'non-local search', which may give rise to radical breakthroughs (Laursen, 2012). Numerous important technical inventions were the result of advances in scientific knowledge resulting from basic research.[1]

To what extent it is rational for firms to carry out basic research themselves has been subject of a long debate among economists. Nelson (1959) argues that firms are reluctant to invest in basic research due to high degrees of uncertainty, long time frames to bear fruit, and limited opportunities for appropriation. The latter results from the fact that the outcome of basic research, i.e. knowledge, is believed to be (at least partly) a public good and therefore freely available to other firms, including those that did not invest in basic research themselves (Arrow, 1962). Rosenberg (1990), on the other hand, argues that, despite these difficulties, there are rational reasons for private firms to conduct basic research with their own money. First, firms that perform basic research may benefit from first-mover advantages in terms of access to new scientific knowledge, and enhance their technology development activities through a deeper understanding of the phenomena under study, resulting in new innovations. Second, basic research investments can help firms to develop the absorptive capacity to monitor, interpret, appraise, and utilize findings emanating from basic research conducted outside the firm.

In reality, firms invest significant amounts of money in basic research. In 2015, US firms invested altogether close to $16 billion in basic research, representing 19% of total investments in

basic research in the US economy. The relative importance of basic research in total R&D expenditures of firms has however declined over time, from 7 percent in 1991 to 5.5 percent in 2015.[2] Several explanations have been put forward to explain this decline (especially in the 1990s and 2000s), such as increased opportunities to tap into external basic research conducted by universities and start-ups and growing appropriation problems due to increased competition and knowledge spillovers (Arora *et al.*, 2018; Arora *et al.*, 2020; Arora *et al.*, 2021).

Extant literature (Gambardella, 1992; Cockburn and Henderson, 1998; Fabrizio, 2009; Della Malva *et al.*, 2015) has shown that firms can improve their innovation performance by investing in basic research. Lacking in prior studies is however an explanation and analysis of *how* investments in basic research enhance the effectiveness of firms' innovation efforts. We contribute to the literature by disentangling two mechanisms through which investments in basic research affect technology development, namely: 1) by strengthening the firm's absorptive capacity to build on externally conducted basic research (we label this *building on external basic research*), and 2) by serving as a direct input to firm innovation (we label this *building on internal basic research*). We model and test these two mechanisms as mediating the relationship between firms' internal basic research endeavours and their innovation performance. We study the relative importance of both mechanisms and examine whether their importance has changed over time.

We rely on a 21-year panel dataset (1995-2015) on the patent and publication activities of the largest 50 pharmaceutical firms in the world by R&D expenditures. An empirical contribution of our study stems from the use of accurate indicators of basic research. Prior studies (e.g. Gambardella, 1992; Cockburn and Henderson, 1998; Fabrizio, 2009) have predominantly used either the total number of corporate scientific publications as a proxy for investments in basic research, or references to scientific articles in patents as a proxy for the use of basic research findings in technology activities.[3] However, scientific articles are an imperfect measure of basic research because a large share of these articles report on applied research, which in the context of the pharmaceutical sector often refers to clinical trials (Hicks et al., 1994). Using information on

the journals in which firms' scientific articles are published and the CHI classification scheme for basic versus applied research (Hamilton, 2003), we construct indicators of basic research by relying on the subset of scientific articles appearing in journals that report on basic research. More specifically, internal basic research is measured using a firm's publications in basic research journals, while building on internal and external basic research in technology development is captured by references in a firm's patents to internal and external basic research publications. We note that we take an inclusive approach to basic research activities conducted by firms, including collaborative research leading to articles co-authored by the firm and university or other partners. External basic research is research with no focal firm involvement.

We find that the relationship between basic research and innovation performance is significantly, but only partially, mediated by the direct contribution of in-house basic research to innovation and the leverage of external basic research in technology development, with a stronger weight for the latter absorptive capacity mechanism. The mediation relationships are much more pronounced in the last 10 years of the panel, with in particular the mechanism to directly build on internal basic research in technology development increasing in importance. While traditionally firms invested in basic research mainly to be "plugged in" to the scientific community (Rosenberg, 1990; Cockburn & Henderson, 1998; Arora *et al*, 2018), nowadays basic research is increasingly used as a direct input to innovation. Interestingly, this pattern is observed against the backdrop of declining basic research by firms, which suggests a more targeted approach aimed at getting more leverage out of a smaller commitment to basic research. By unpacking two key mechanisms for basic research investments to improve firms' innovation performance, our results provide a more detailed understanding of the (changing) rationale for basic research in firms in the context of declining corporate basic research investments.

The Importance of Basic Research for Industrial Innovation

Basic research has received many definitions (Rosenberg, 1990). We adopt the definition of the National Science Foundation (NSF) where basic research is defined as "the systematic study

directed towards greater knowledge or understanding of the fundamental aspects of phenomena and observable facts without specific immediate commercial applications in mind, although research may be in fields of present or potential commercial interest of those performing the research activities" (NSF, 2009). Applied to the pharmaceutical industry, basic research aims to reveal the mechanisms and processes of diseases, but does not include applied research activities such as compound screening, clinical trials and dosage testing (Lim, 2004).

Basic research conducted by firms is concentrated in two different respects. First, a major part of basic research is conducted in a small number of industries such as pharmaceuticals, chemicals, electrical machinery and aerospace (Mansfield, 1980; Rosenberg, 1990). These sectors are called 'science-based industries' in Pavitt's (1984) classical sector taxonomy. Second, within these sectors a handful of firms are responsible for a large share of basic research. These firms are typically large, with broad product and technology portfolios and operating large R&D laboratories. Such firms are more confident that they will be able to put both anticipated and unexpected findings from basic research into commercial use (Nelson, 1959).

For private firms, basic research is a process of learning of the physical world that generates knowledge on which they can draw in their technology development activities (Klevorick *et al.*, 1995; Matutes *et al.*, 1996; Malo, 2009; Toole, 2012). Mansfield (1995 & 1998) examined the importance of basic research for firms' innovation activities by surveying samples of US firms across different industries. He found that, during the period 1975-1985, 11% of firms' new products and 9% of new processes could not have been developed (or with substantial delay) in the absence of basic research conducted by universities. These numbers were higher for the period 1986-1994 (respectively 15% and 11%), suggesting that basic research increased in importance for industrial R&D. A possible reason for the increasing importance of basic research may be found in the increasing complexity of products and production processes in most industries (Rycroft and Kash, 1999). Another indication of the growing reliance of industrial innovation activities on (basic) scientific knowledge can be found in the analysis of citations to scientific literature in patent

documents (Narin *et al.*, 1997; Arora *et al.*, 2018; Marx and Fuegi, 2020). Analysing citations to scientific publications in USPTO patents between 1947 and 2020, Marx and Fuegi (2020) found that while USPTO patents before 1980 had less than one citation to science on average, this number increased to more than four citations per patent in 2020.

Several patent-level studies have examined the effect of the use of scientific research findings, measured by citations to scientific literature in firm patents, on the value of firm innovations, measured by forward citations of patents. Fleming and Sorenson (2004) identified a positive relationship between patent value and citations to scientific literature in fields where technology development is complex. Nagaoka (2007) similarly found a positive relationship between Japanese firms' patent citations to scientific literature and the forward citations these patents receive in both the IT and pharmaceutical sectors. Using data on patents of US approved drugs, Sternitzke (2010) found that radical innovations build more on basic scientific knowledge than incremental innovations.

A related set of studies examined the use of science at the firm level rather than at the patent level and has suggested that the most robust relationship with firm innovation is at the broader firm level. For a sample of Belgian firms, Cassiman *et al.* (2008) did not find support for an association between citations to basic scientific research and innovation performance at the patent level, but found such an association at the firm level, using measures of formal linkages to science and firm engagement in scientific research. Branstetter and Kwon (2004) conducted firm-level analyses and found that firms citing more science in their patents achieve a higher innovation performance, as measured by their citation-weighted patent output. While this literature has confirmed that firms draw on, and benefit from, basic research, it has not juxtaposed the use of external versus internal basic research, or to what extent drawing on basic research is driven by a firm's own basic research efforts.

A parallel stream of research has focused on the role of in-house basic research investments in strengthening corporate innovation performance. Gambardella (1992) and

Cockburn and Henderson (1998) found that pharmaceutical firms that perform more basic research (measured by the number of firm publications) produce a greater number of patented inventions. Using a sample of both pharmaceutical and biotechnology firms, Fabrizio (2009) found a positive association between in-house basic research and the quality of firms' patents. In contrast, Lim (2004) found no effect of in-house basic research on the patent performance of pharmaceutical firms, and even a negative effect for semiconductor firms, but his analysis could not control for differences in firms' R&D inputs, which may partly explain the differences in results. Della Malva *et al.* (2015) observed that pharmaceutical firms pursuing basic science are more likely to produce breakthrough inventions. Again, this effect plays out at the firm level rather than the technology level, consistent with the view of 'science as a map' to guide processes of search across domains rather than affecting breakthroughs within more narrowly defined technological domains. Although this literature has established a positive relationship between in-house basic research and firm innovation performance, extant studies have not examined the mechanisms through which these performance benefits occur.

In conclusion, while prior work has devoted ample attention to the role of (basic) scientific research in corporate innovation, both in terms of the engagement in basic research and in the usage of basic research, it has not examined the key mechanisms and conduits through which basic research investments can affect technology development. In this paper, we examine two key mechanisms and argue that basic research investments can improve a firm's innovation performance by strengthening the firm's absorptive capacity to build on externally conducted science, and by serving as a direct input into firm innovation. Following the findings of prior studies, we consider basic research at the broader firm level. We consider investments in in-house basic research as an antecedent to the use of basic research in technology development, suggesting that the relationship between in-house basic research and firm innovation performance is mediated by the use of internal and external basic research.

Hypotheses

Informed by prior conceptual and empirical contributions, we first formulate a baseline hypothesis on the association between performing in-house basic research and innovation performance. We then formulate two mediating hypotheses on the mechanisms through which the firm can leverage basic research in its technology development (H2 and H3).

Benefits of Internal basic Research for Innovation Performance (baseline hypothesis)

Firms that perform basic research can benefit from the scientific knowledge that is generated by these research activities in several ways. First, basic scientific knowledge can serve as a map of the technological landscape, which guides firms towards the most promising applied research directions (Rosenberg, 1990; Fleming and Sorenson, 2004). Internal basic research capabilities may also act as an admission ticket to R&D partnering with universities and public research organizations (Belderbos, 2004; Liebeskind *et al.*, 1996; Cockburn and Henderson, 1998; Murray, 2004; Belderbos et al., 2016). Internal basic research demonstrates the scientific competences firms need in order to enter into relationships of information exchange with public sector scientists (Hicks, 1994). Collaboration with university scientists often leads to extensive debate and exchange of ideas (Almeida *et al.*, 2011). This provides firms with access to tacit knowledge of university scientists, which is not provided in journal articles (Arora and Gambardella, 1990), and which allows them to build faster on recent basic research findings by accessing university research that is not yet published (Fabrizio, 2009).

Internal basic research may also act as a powerful recruiting tool, since the scarce, highest quality researchers ('stars') are reluctant to work for firms in which they are not allowed to do basic research and publish scientific findings (Henderson and Cockburn, 1994; Hicks, 1999; Narin & Breitzman, 1995). Publishing is one of the most important means for scientists to establish their reputation (Stephan, 1996), and corporate scientists have even been found to accept lower wages in exchange for the permission to conduct and publish scientific research (Stern, 2004). From the perspective of an innovating firm, the scarcity of high-quality (star) scientists[4] implies that

accessing the best human capital through hiring is of strategic importance (Hess and Rothermael, 2011; Zucker *et al.*, 2002; Furukawa and Goto, 2006). Finally, by investing in basic research, firms build up the necessary capabilities to monitor, evaluate and exploit basic research that is conducted elsewhere. Firms need to invest in an absorptive capacity to build on scientific knowledge (Rosenberg, 1990; Cohen and Levinthal, 1989).

Overall, the preceding arguments suggest a positive association between basic research investments and innovation performance, formalized in the following baseline hypothesis:

Hypothesis 1 (baseline): Performing basic research internally has a positive association with firms' innovative performance.

Internal Basic Research to Improve the Absorption of External Basic Research in Technology Development

External basic research findings are not a free input to firms' own research activities (Rosenberg, 1990). As Cohen and Levinthal (1990) have noted, learning is a cumulative, incremental process that is influenced by capabilities that are already present at the individual and organizational level. Individuals learn through a process whereby new events are stored in their memories by establishing linkages with pre-established concepts and ideas. An organization's ability to learn depends, at least in part, on the ability of its individual members to learn, as organizational learning involves the joint contributions of individual members to solve problems (Helfat, 1994). The ability of organizations to learn from external research findings depends on the commonality between the organizations' internal knowledge base and the external research findings that firms intend to build on in their technology activities (Teece *et al.*, 1997).

Firms that want to take advantage of research conducted outside their organizations need to invest in an 'absorptive capacity' in the sense of accumulating knowledge and skills to identify, understand and utilize externally generated knowledge (Cassiman and Veugelers, 2006; Lokshin *et al.*, 2008). The creation of an 'absorptive' capacity for external basic research findings involves the employment of a cadre of scientists and granting them the freedom to perform basic research

(Rosenberg, 1990; Pavitt, 1991). These scientists can function as 'gatekeepers' to bridge the external scientific community and corporate technologists (Allen, 1977). Based on the absorptive capacity argument, firms that perform more basic research will be better equipped to build on and benefit from external basic research in their technology activities. According to Arora *et al.* (2018) the absorptive capacity function of basic research has become more important over time due to a "thickening of the supply side of basic research" with universities and small firms actively looking for opportunities to transfer basic research findings to large firms.

In sum, firms may reap the benefits of performing basic research in-house through a greater capability to build on external basic science in their technology development efforts. This suggests the following mediation hypothesis:

> *Hypothesis 2: The positive association between internal basic research and firm's innovative performance is partially mediated by an enhanced capability of the firm to build on external basic research in technology development.*

Basic Research Serving as a Direct Input into Technology Development

Investments in basic research do not only function as a gateway to findings of externally conducted basic research, but can directly feed into a firm's technology development (Arora *et al.*, 2021). Firms that perform basic research may also generate a first mover advantage in terms of access to unique scientific knowledge (Rosenberg, 1990). Just like external basic research findings cannot be assimilated in a costless fashion, internally performed basic research does not seamlessly enter a firm's technology development. In order to benefit from its investments in basic scientific research, a firm needs to process, recombine and translate the scientific knowledge before it can be applied in technology development (Furman & Stern, 2011). Firms can actively facilitate this process by creating reward structures that stimulate scientists to direct their scientific search towards more applicable ends (Lerner and Wulf, 2007) and to actively transfer basic scientific knowledge to technical personnel (Gassman & von Zedtwitz, 1999).

In the context of the pharmaceutical industry, conducting basic scientific research internally will facilitate dealing with the crucial 'translation' from basic laboratory work to clinical trials (Woolf, 2008; Bhogal and Balls, 2008). Such 'translation' is found to be crucial for drug development success, and will be more effective if the R&D organization engaging in it is also involved in the discovery of the drug compound. Drug development often fails because of insufficient attention given to research on effectiveness, dosage, and transportation inside the human body (Pisano, 2006). Being part of the same firm fosters close and frequent interactions that build trust between the basic research scientists and clinical scientists (Hoegl and Proserpio, 2004), which has been found to play a key role in the willingness of researchers to share their knowledge and experience (Szulanski, 1996; Mooradian et al., 2006) and hence facilitates the translation of basic research into technology development. If firms can effectively build on internal basic research at the forefront of scientific development, they are likely to capitalize on their first mover advantage in knowledge in the creation of valuable innovations (Fabrizio, 2009).

It follows that a second channel through which firms may reap the benefits of performing basic research in-house is through greater opportunities to build on internal basic science in their technology development efforts. This suggests the following mediation hypothesis:

> *Hypothesis 3: The positive association between internal basic research and firm's innovative performance is partially mediated by an enhanced capability to build on internal basic research directly in technology development.*

Empirical Analysis

Before we describe the characteristics of the dataset, it is useful to give attention to the context of our analysis: the role of basic research in the global pharmaceutical industry. We focus on the pharmaceutical industry, since this is a science-based industry where basic research plays an important role in innovation (McMillan *et al.*, 2000; Pavitt, 1984; Pisano, 2010). Patents in drugs and medicine classes cite significantly more scientific articles than patents in other classes (Narin *et al.*, 1997) and cite basic scientific research more heavily (Narin and Olivastro, 1992). The strong

reliance of pharmaceutical firms on basic research becomes also apparent from the case histories of the discovery of 21 important drugs documented by Cockburn and Henderson (1998). Fundamental insights in basic research played a role in the discovery of sixteen of these drugs. Using data on the U.S. National Institutes of Health (NIH) biomedical research awards from 1955 to 1996, Toole (2012) found a positive effect of public basic research on pharmaceutical drug discovery. Moreover, the link between basic research and drug discovery has increased over time (Lim, 2004). Pharmaceutical firms have moved away from randomly screening a large number of potentially useful compounds against a certain disease, towards a more systematic approach called 'rational drug design'. This approach involves building on knowledge about the biochemical mechanisms causing a disease, in order to identify and develop chemical or biological compounds that inhibit the biochemical mechanisms causing a disease (Pisano, 1997).

Basic research has become part of the drug discovery process in most pharmaceutical firms. Based on case studies of US pharmaceutical firms, Gambardella (1992) has however shown that pharmaceutical firms pursue different strategies with respect to the importance given to basic research. For example, while Merck invested strongly in basic research in the 1980s and used this knowledge to further build on externally generated basic research findings, Bristol-Myers invested significantly less in internal basic research during the same period. Using publication data from 1989, Hicks (1994) showed differences in engagement in basic research across Japanese pharmaceutical firms, with Takeda investing substantially more in scientific research than Kyowa Hakko Kogyo and Ajinomoto.

Sample and Dependent Variable

We constructed a panel dataset on the patent and publication activities of the 50 largest R&D spending pharmaceutical firms in the world. In the pharmaceutical industry there are two different types of firms: large pharmaceutical firms and, usually smaller, biotechnology firms. We focus on the top R&D spending pharmaceutical firms in the world because they dominate R&D expenditures, patenting and publishing efforts in the industry. In line with prior studies, we expect

substantial heterogeneity in R&D strategies and the importance given to basic research among pharmaceutical firms. In contrast, biotechnology firms often originate from scientific research at universities and public research institutions such that the degree of involvement in basic research will be a less distinctive characteristic, while the smaller scale operations may render it more difficult to construct reliable basic research indicators over time.

The sample firms are selected as the top R&D spending pharmaceutical firms from the '2004 EU Industrial R&D Investment Scoreboard'. This scoreboard lists the top 500 corporate investors in R&D whose parent is located in the EU, and the top 500 companies whose parent is located outside the EU (mainly US and Japan), based on corporate R&D expenditures in 2003. The sample firms, together with their home countries, are listed in the appendix. The sample firms are observed for a maximum period of 21 years (1995-2015). The panel is unbalanced because some firms are formed by a large merger after 1995 (e.g. AstraZeneca was created by the merger of Astra and Zeneca in 1999, and is included in the dataset from 1999 onwards) or have been acquired by other firms in the sample period (e.g. Schwarz Pharma was acquired by UCB in 2006, and is included in the dataset until 2005) and because in a few cases R&D data are not available for the entire period.

Our measure of the innovative performance of the firms is based on patent data. There are numerous advantages of the use of patent indicators (Pavitt, 1985; Basberg, 1987; Griliches, 1990): patents contain detailed information on the owners and prior art of patented inventions; patent data are objective in the sense that they have been processed and validated by patent examiners; and patent data are easily available from patent offices and cover long time series. Like any indicator, patent indicators are also subject to a number of drawbacks: not all inventions are patented and those that are patented vary in their technical and economical value (Trajtenberg, 1990; Lanjouw *et al.*, 1998; Gambardella et al., 2008). The first problem can be addressed by limiting patent analyses to industries with high patent propensities and studying firm-level patent time series. The majority of inventions in the pharmaceutical industry are patented (Arundel and Kabla,

1998; Campbell, 2005) and firm-specific patent application policies are likely to be relatively stable over time. The 'value' problem can be taken care of by weighting patent counts by the number of forward patent citations received by these patents (Trajtenberg, 1990; Harhoff *et al.*, 1999; Hall *et al.*, 2005). Both approaches are followed in this paper.

Since company names in patent databases are not unified and patents may be applied for under names of subsidiaries or divisions of a parent firm, we collected patent data at the consolidated parent firm level. Therefore, we searched, for each parent firm, for patents under the name of the parent firm as well as all their majority-owned subsidiaries. For this purpose, we relied on information from *Orbis Historical* and M&A data from *Thomson Reuters SDC Platinum* and *Zephyr* by Bureau van Dijk, complemented with corporate annual reports, yearly 10-K reports filed with the SEC in the US. For Japanese firms, we also used information on foreign subsidiaries published by Toyo Keizai in the yearly 'Directories of Japanese Overseas Investments'. The consolidation was conducted on a yearly basis to take into account changes in the group structure of sample firms due to acquisitions, mergers, green-field investments and spin-offs. Acquisitions, and their patent stocks, are considered part of a parent firm from the year the acquisition transaction has been completed.

Patent data are taken from the PATSTAT database (version May 2018). The innovative performance of the sample firms (dependent variable) is measured as the number of PATSTAT patent families that are filed by a parent firm in a year, weighted by the number of forward patent citations received by those patents over a fixed time window of 4 years. In particular, in the pharmaceutical industry, patents and patent citations are a relevant indicator of innovative performance and are closely linked to market valuation (Deng *et al.*, 1999, Harhoff *et al.*, 2003, Hall *et al.*, 2005, Nagaoka, 2005). Magazzini *et al.* (2012) show that patents protecting chemical compounds that successfully get through clinical trials receive significantly more citations than patents pertaining to compounds that fail in initial trials (but often get a second life in another application), while patented compounds that do not make it to such trials receive no or much

smaller numbers of citations. The number of forward patent citations is calculated on a fixed 4-year time window in order to have a comparable citation window for all patents (Hall *et al.*, 2005; Trajtenberg, 1990). Forward patent citations are calculated on the PATSTAT database and have been de-duplicated at the family level to avoid double counting.

Internal Basic Research

We use information on scientific publications authored by the sample firms and published in peer reviewed international journals to assess firms' engagement in basic research. Prior work has argued that publication counts represent investment levels in (basic) science and proxy for the extent to which company scientists are linked to the scientific community (Gambardella, 1992, 1995; Cockburn and Henderson, 1998). In addition, publication rates are a timely measure of pharmaceutical firms' involvement in basic research, since the turn-around time of publications in pharmaceutical fields is short (Kaplan *et al.*, 2003).

Publication data are extracted from yearly updates of the Science Citation Index database of Clarivate Analytics. Publication data is collected at the consolidated parent firm level, following a similar approach as the one followed for the collection of patent data. This approach consists of identifying all publications on which the parent firms, or their subsidiaries, are listed as author affiliations. The consolidation exercise is conducted annually. In line with studies of Hicks *et al.* (1994) and Cockburn and Henderson (1998) we find that pharmaceutical firms publish extensively: the sample firms published on average 228 publications per year in the SCI database over the period 1991-2015. We collected bibliographic information (journal name, volume, pages etc.) for all the publications on which the 50 sample firms are listed as one of the authors' affiliations. We take an inclusive approach to basic research activities conducted by firms, counting all publications of the focal firms, single authored or co-authored with other firms, universities, or research institutes. Co-authorship indicates a clear involvement in the basic research, which is expected to yield the benefits discussed in the theory, such that internal basic research should not be understood as restricted to basic research performed *exclusively* by the firm.

We classified a publication as 'basic research' based on the journal in which it is published. The CHI journal classification scheme classifies each of the SCI journals in one of four research levels, in a spectrum ranging from very applied, targeted research to basic research. For biomedical journals the four different research levels are called 'clinical observation' (level 1), 'clinical mix' (level 2), 'clinical investigation' (level 3) and 'basic biomedical research' (level 4).[5] Journals that are classified in level 4 are considered as reporting basic research findings. Applying the CHI classification scheme, about 29% of the SCI publications of the sample firms are published in basic research journals and are used in the construction of the basic research variables.

To allow for a time lag between internal basic research and firms' innovative performance in year t, internal basic research is measured over the prior 4-year period. The variable *internal basic research* is calculated as the sum of firm publications in basic research journals in the past 4 years (t-4 to t-1) by the firm or its subsidiaries in year t. We have log transformed this variable to improve the interpretation as an elasticity in the analyses.[6]

Mediators: Building on Internal and External Basic Research

Our two mediating variables measure the extent to which firms build on internally performed and externally conducted basic research in their technology activities, and are based on references to publications in basic research journals in the prior art of firms' patents. The prior art section of a patent contains references to prior patents and non-patent literature, including scientific publications. References to scientific publications include publications by the firm itself as well as publications by external parties. The legal purpose of the references is to indicate which parts of the knowledge described can be claimed by the patent and which parts have been claimed by prior patents and non-patents. For instance, Strumsky and Lobo (2015) state that *"prior art citations […] are made to delineate a patent's claims of inventive originality and bound the scope of legal protection sought by the proposed invention"*. Patent references restrict the scope of patent claims to novelty and represent a link to the pre-existing knowledge base upon which patents have been built (Criscuolo and Verspagen, 2008; Czarnitzki *et al.*, 2020; Jaffe *et al.*, 2004; Marx and Fuegi, 2020). This feature has

been used by prior studies (e.g. Narin *et al.*, 1997; Fleming and Sorenson, 2004; Cassiman *et al.*, 2008; Belderbos *et al.*, 2017; Arora *et al.*, 2018; Arora *et al.*, 2021) to justify the use of patent references as an information source on the knowledge base of patent applicants.

One critique on this particular use of patent references is that the prior art section of patents includes not only references provided by patent applicants but also those added later by patent examiners during their search for relevant prior art (Alcacer and Gittelman, 2006). Therefore, patent applicants may not know part of the references cited in the prior art of their patents (Brusoni *et al.*, 2005). However, surveys of USPTO patent inventors (Jaffe *et al.*, 2004; Fleming and Sorenson, 2004; Tijssen *et al.*, 2000) have shown that inventors are aware of a significant part of the patents and scientific articles that are cited in the prior art of their patents, including references made by patent examiners. Among all references on patents, references to scientific articles are more frequently added by patent applicants themselves (Narin and Noma, 1985; Jaffe *et al.*, 1998; Marx and Fuegi, 2020), which explains a relatively high degree of familiarity of patent inventors with scientific articles cited on their patent documents. Fleming and Sorenson (2004) and Tijssen *et al.* (2000) report, in their respective surveys, that patent inventors are aware of 62% and 84% of the cited articles in their patents. Using data on EPO patents and responses to the Community Innovation Survey (CIS) for a sample of French firms, Duguet and MacGarvie (2005) find a positive correlation between the number of references in firms' patents and the intensity to which firms have sourced external knowledge. Using information from the Carnegie Mellon Survey for a sample of US firms, Arora *et al.* (2021) find that firms whose patents cite scientific literature also reported that science contributed to their R&D projects. Furthermore, Arora *et al.* (2021) observed that the scientific fields that contributed most to firms' R&D projects are also the fields most cited in firms' patents. We consider this sufficient evidence to take scientific references on patents as an (imperfect) indicator of the scientific knowledge base that firms were able to build on in their drug development activities.

Non-patent references were extracted from the PATSTAT database for all the patents of the sample firms. We have used non-patent references to scientific articles in basic research journals in the calculation of our firm-level mediating variables *building on internal basic research* and *building on external basic research*. These references are identified via a text-matching algorithm and the CHI list of all research journals (applied/basic) in the SCI database. Specifically, non-patent references (NPRs) to scientific articles in the SCI database are identified by examining the presence of SCI journal names (6,400 journals) in the text strings of the NPRs on the patents. About 30% of these non-patent references referred to publications in scientific journals (SCI database); 37% of these scientific non-patent references referred to publications in basic research journals. These numbers are comparable with numbers found in prior studies on non-patent references (Harhoff *et al.*, 2003; Callaert *et al.*, 2006).

We separated NPRs referring to basic research publications of the firm itself from references to external basic research by using information on the *journal name, volume*, *year* and *starting page* of the publication to which a scientific NPR refers. An NPR was considered to refer to a basic research publication of the firm itself when the journal name, volume, year and starting page in the NPR text were identical to one of the publications authored by the firm in the period 1991-2015.[7] On average, 2.8% of the citations to publications in basic research journals referred to publications of the citing firm. The basic scientific references that do not refer to publications of the citing firm are classified as external basic research.

The variable *building on internal basic research* is calculated as the number of citations to basic research publications of the firm itself in patents applied for by the firm (or its subsidiaries) in the past 4 years. The 4-year prior period allows for a time lag between the exploitation of external basic research and firms' innovative performance in year t. Consistent with the inclusive approach to the measurement of in-house basic research conducted by the firm, this variable includes publications that the firm co-authored with external partners. The variable *building on external basic research* is defined in a similar way as the number of citations to external basic research publications

in patents applied for by the firm (or its subsidiaries) in the past 4 years.[8] Both mediating variables have been log transformed, after adding a value equal to one.

Control Variables

Our empirical models control for a number of (time varying) firm-level factors that are likely to influence firms' innovative performance. First, we control for differences in the scale of the firms' *R&D expenditures*, by including the one-year lagged R&D expenditures (expressed in natural logarithm) in the regressions. Hall *et al.* (1983) studied the time lag between R&D and patent applications, and found that most of the effect of R&D on patents happens within the first year after the R&D expenses are made. The data on firms' R&D expenditures are collected from corporate annual reports and financial databases (Worldscope and Compustat) and are measured in millions of US dollars.

Second, we distinguish firms' overall *propensity to publish* from their engagement in basic research activities, by controlling for the ratio of total firm publications to basic research publications, measured over the prior 4-year period.[9]

Third, we include an indicator for the level of *technology diversification* in a firm's patent portfolio, such that both the scale and scope of R&D activities of firms are controlled for (Arora *et al.*, 2009; Henderson and Cockburn, 1996; Nesta and Saviotti, 2005; Leten *et al.*, 2007). Technology diversification is measured as the 'spread' of firm patents over the past 4 years over technology classes. Technology class information on patents is derived from the IPC classes assigned to patents. We distinguish between 120 different 3-digit IPC classes to construct the diversification measure. The technology diversification variable is calculated as a Blau index (minus the Herfindahl index): it takes higher values when the level of technology diversification increases. We tested for both linear and quadratic relationships between technology diversification and innovative performance. The relationship turned out to be distinctly linear in our sample and we therefore only included a linear term of technology diversification in the reported analyses.

Fourth, we control for the extent to which firms *focus on biotechnology* in their technology development. Prior research (e.g. Birkinshaw *et al.* 2018) has documented that pharmaceutical companies have adopted different strategies in terms of the timing of entry and the commitment to biotechnology, resulting in different innovation performance outcomes. A firm's focus on biotechnology is measured as the share of biotechnology patents in a firm's four-year patent portfolio. To identify biotechnology patents, we rely on the Fraunhofer-INPI-OST technology classification that assigns patent IPC classes to 30 different technology fields, including biotechnology.

Fifth, we include an indicator that captures the involvement of firms in *R&D collaborations*. By collaborating with external parties, firms can get access to complementary knowledge (Belderbos et al., 2021; Du *et al.*, 2014; Faems *et al.*, 2005; Belderbos et al., 2004) and may improve their innovative performance. We identify collaborations using the Thomson Reuters RECAP database, which includes information on transactions (including collaborations) in the life sciences industry. Our measure of collaborations is constructed at the consolidated firm level and includes cooperation on R&D and co-development activities. The variable *R&D collaboration* is constructed as the log of the ratio of the number of collaborations in the prior 4 years and the size of the firm's R&D expenditures in year t-1 to make it independent of the scale of a firm's R&D activities.

Finally, the empirical models include 20 year dummies (with 1995 as base category) to account for time-specific factors affecting the innovative performance of the sample firms.

Methods

Count data models are preferred to standard linear regression models for our analysis, as they explicitly take into account the non-negativity and discreteness of the dependent variable (a citation-weighted patent count). We use negative binomial count data models, which control for over-dispersion of the dependent variable (Cameron and Trivedi, 1998). We use firm fixed effects estimators in all regression models to control for unobserved, time-invariant firm characteristics that could affect innovative performance, such as R&D management capabilities. We estimated

fixed effects negative binomial models by including dummy variables for all firms, as suggested by Allison (2012).[10] Besides including fixed effects, our empirical specification has other features that alleviate concerns of potential endogeneity and bias stemming from unobserved heterogeneity. First, the temporal ordering of the variables in the model - where past publication and scientific patent citation counts are included to explain current performance – avoids reverse causality, where higher innovation performance and the ensuing higher availability of R&D resources may lead to increased investments in basic research. Second, we include time-varying firm characteristics as control variables (R&D expenses, propensity to publish, technology diversification, biotech focus, R&D collaboration) that are likely to pick up important developments in corporate R&D resources and capabilities.

We estimate the first stage of the mediation model in which *building on internal basic research* and *building on external basic research* are dependent variables with fixed effects ordinary least squares regressions. To test for mediation, we estimate a structural equation model (SEM) that allows for correlation between the two mediation routes. To relax the assumption of multivariate normality of the Baron and Kenny (1986) test for measuring indirect effects, we bootstrap the standard errors using 400 repetitions (Cole and Maxwell, 2003).

Descriptive Statistics

Summary statistics and correlation coefficients are reported in Table 1. Correlation coefficients are calculated as within-firm correlations, consistent with the fixed-effects estimators used in the empirical analysis. The correlations provide some prima facie evidence of the hypothesized relationships. There is a positive correlation (a correlation coefficient of 0.21) between internal basic research and a firm's innovative performance (baseline hypothesis 1). Internal basic research positively correlates with both *building on internal basic research* and *building on external basic research*, which in turn each have a positive correlation with firm's innovative performance.

Insert Table 1 about here

Figure 1 reports the evolution in internal basic research as well as firms' building on internal and external basic research over the period 1995-2015 for the set of firms that are observed every year. In line with the operationalization of the variables used in the regression models, the reported numbers are based on 4-year stocks of publications and scientific references. Firms' investments in internal basic research were high at the beginning of the time period (277 publications in 1995), remained stable during the first half of the period, but started to decline monotonically from 2005 onwards to reach 150 publications in 2015. In contrast to the declining trend in internal basic research, the sample firms strongly increased the extent to which they build on both internal (from 8 to 128 citations) and external basic research (from 200 to 3,107 citations) in their technology development. The strong increase in the number of internal and external basic research citations is mainly the result of a strong increase in the number of scientific citations in firms' patents, since the size of firms' 4-year patent stock only increased by 35% between 1995-2015. The overall pattern of a decreasing intensity of in-house basic research coupled with an increase in the extent to which companies build on basic research in technology development is consistent with the evidence reported by Arora *et al.* (2018) and Arora *et al.* (2021) for large, cross-sectoral samples of US firms.

Insert Figure 1 about here

Empirical Results

The results of the fixed effects models of the relationship between internal basic research, building on internal and external basic research and firms' innovative performance are reported in Table 2. Model 1 includes the control variables only and shows that *R&D expenditures*, *technology diversification* and *biotech focus* are positively associated with performance and are statistically significant at the 1%

level. The coefficients of the *collaboration* and *propensity to publish* variables are not significant at the 10% level.

Insert Table 2 about here

In model 2, we test our baseline hypothesis 1 by adding the variable *internal basic research*. A log-likelihood ratio test indicates that the model fit improves significantly by adding this variable (chi^2=44.74, p=0.000). In line with hypothesis 1, we find a positive and significant association between *internal basic research* and firms' innovative performance. The strength of the relationships can be derived directly from the estimated coefficient (0.231), which can be interpreted as an elasticity. This implies that a one percent increase in performing basic research is associated with a 0.231 percent increase in firm's innovative performance.

To test for the mediation effects suggested by hypotheses 2 and 3, we estimate a generalized structural equation model (SEM), allowing for correlation between the error terms of the two mediation equations. Models 3a and 3b test whether *internal basic research* is significantly related to *building on internal basic research* and *building on external basic research*. The coefficient of *internal basic research* is positive and significant in both models. This shows that firms that perform more basic research in-house also build more on internal and external basic research in their technology development. Furthermore, we observe that firms that focus more on biotechnology build more on internal and external basic research in their technology activities. While technology diversification has a positive association with *building on external basic research*, it has a negative association with *building on internal basic research*. Model 3c assesses whether the mediator variables (*building on internal basic research* and *building on external basic research*) are significantly related to a firm's innovative performance, controlling for the direct effect of internal basic research. The coefficients of both mediators are positive and significant. The coefficient of *internal basic research* declines when we add the mediators (relative to model 2), but it remains significant in the full innovation

performance model 3c, with an elasticity equal to 0.16. Given that *internal basic research* has a positive association with *building on internal basic research* and *building on external basic research* (models 3a-3b) and given that *building on internal* and *building on external basic research* are both associated positively with firm's innovative performance when controlling for *internal basic research*, we can confirm our two mediating hypotheses 2 and 3. As the coefficient of *internal basic research* is still positive and significant in model 3c, the mediation is partial.

To assess the effect size of mediation relative to the direct effect of *internal basic research*, we examine the magnitude of effects using elasticities as a scale-free measure. The simultaneous estimation with the SEM model allows for a direct test of the significance of the two mediation paths. The estimated elasticities reflecting the proportional changes in firm's innovative performance as a result of a proportional change in *internal basic research* mediated by respectively *building on internal basic research* and *building on external basic research* are 0.011 (statistically significant at the 10% level, p=0.066) and 0.065 (statistically significant at the 1% level, p=0.000), while the elasticity corresponding to the direct effect of *internal basic research* is 0.156.[11] Hence, 33% of the total effect of *internal basic research* is jointly mediated by *building on internal basic research* and *building on external basic research*. This result indicates that explicitly building on own research and leveraging external basic research in the technology process jointly account for one third of the total benefit of a firm's investment in basic research.

We further examined whether the relative importance of the two mediation mechanisms has changed over time. For this purpose, we estimated separate coefficients for the basic research variables for the first half (period 1: 1995 to 2005) and second half (period 2: 2006 to 2015) of the observation period. The results are reported in Table 3. We observe in model 2 that the association between *internal basic research* and firm's innovative performance is weaker in period 2 than in period 1. While in both time periods the relationship between *internal basic research* and firm's innovative performance is mediated by both *building on internal basic research* and *building on external basic research*, the mediation effects are stronger in period 2 (full mediation) than in period 1 (partial mediation).

The magnitude of the first mediation mechanism (*building on external basic research*) is comparable in both periods, but the second mediation mechanism (*building on internal basic research*) becomes much stronger in the second period. While in the first period, mediation through *building on internal basic research* accounts for only 13.1% of the mediation effect (statistically insignificant at the 10% level, p=0.104), this share increases to 35.8% in the second period.

Insert Table 3 about here

Conclusion and Discussion

This paper examines how firms can improve their innovation performance by engaging in basic research. We distinguish between two main mechanisms through which basic research can affect technology development: 1) by serving as direct input into own technology development, and 2) by developing an absorptive capacity to tap into external basic research. We model and test the relative importance of these two mechanisms by estimating a mediation model using panel data on the patents and scientific publications of 50 large R&D spending pharmaceutical firms. We find that a positive relationship between firms' engagement in basic research and innovation performance is significantly, but only partially, mediated by these two mechanisms, with the role of leveraging external basic research in this mediation process more prominent.

Interestingly, we find that the mediation relationships are much more pronounced in the recent years of the panel, with in particular the role of innovation building on own scientific efforts increasing. This pattern is associated with a marked decline in basic research efforts of the firms in recent years, while the incidence of citations to basic research in firms' patents has continued to rise. It is perhaps the high cost and complexity of maintaining a science-based research organization (Arora *et al.*, 2018), that has led the world's leading pharmaceutical firms to reduce their involvement in internal basic research, while increasing the focus on the connection between basic research and technology development. Firms increasingly run a tight ship and view scientific

research less as a way to merely remain "plugged in" to the scientific community (Cockburn & Henderson, 1998; Rosenberg, 1990; Arora *et al.*, 2018). Investments in basic research are increasingly considered as a way to generate unique scientific knowledge that can be used in the own technology development process. By trying to get more leverage out of their basic research investments, firms have responded to trends of increasing competition and rising R&D costs (Danzon *et al.*, 2005; Pammolli *et al.*, 2011; Cockburn, 2006).

A key managerial implication of our research is that firms should take a combined approach by investing in in-house basic research aimed at bringing this research to fruition in development, and by leveraging these investments through an informed search for external basic research. Leveraging of internal and external basic research in technology development represents a substantial share of the added value of investments in basic research, hence firms are well advised to use their basic research capabilities as a stepping stone to develop technologies on the basis of external basic research. Regarding the direct effect of basic research as an input to technology development, the implication is that a proper alignment between basic research and development activities is important. Innovative performance may further increase if firms manage to reduce frictions that hinder such alignment. This is consistent with the notion of Rosenberg (1990) that corporate basic research is likely to be sterile and unproductive if it is conducted in a separate unit isolated from the rest of the firm's R&D activities. Following this logic, the effectiveness of internal basic research is expected to increase if it is conducted in close interaction with the work and interests of the firms' engineers. Close exchange between researchers and developers that facilitates the exchange of knowledge (Nonaka, 1994), for instance through the organization of multidisciplinary teams, may be important to achieve such alignment. At the same time, we note that the fact that building on in-house basic research in development activities is only a partial mediation mechanism to arrive at innovation performance cautions against an overemphasis on alignment by cutting investments in basic research drastically. Notwithstanding the increasing role of the direct effect of conducting basic research in-house, we found that the indirect effect of basic

research through the improved leveraging of external basic research in technology development has relatively stronger performance consequences. A possible explanation is that building on external basic research beyond collaboration with external partners – the definition of 'external' in our analysis – implies a more distant form of knowledge sourcing which may result in more novel and valuable knowledge recombination, leading to more highly cited patents.

Our study contributes to the literature on corporate investments in basic research by disentangling and comparing two key mechanisms through which engagement in basic research can improve firms' innovative performance (Rosenberg, 1990; Gambardella, 1992; Cockburn & Henderson, 1998; Della Malva *et al.*, 2015; Arora *et al.*, 2018; Arora *et al.*, 2021) and by demonstrating that the relative importance of both mechanisms has changed over time. Further, our study adds to the literature on search strategies for innovation (Nelson, 1982; Fabrizio, 2009; Fleming and Sorenson, 2004) by confirming the important 'guiding' role of science in the search process for innovation. By investing in basic research, firms can leverage both internal and external scientific knowledge as a 'map' for technology developments. Finally, our study adds to the literature on external learning and 'scientific' absorptive capacity (Cassiman and Veugelers, 2006; Lokshin *et al.*, 2008; Zarah and George, 2002; West and Bogers, 2014; Belderbos et al., 2016; 2017) by demonstrating the importance of internal basic research investments to learn from external basic research findings. The observation that basic scientific knowledge is not freely available to all firms, but only to those who have the right background knowledge and skills, is consistent with Rosenberg's (1990) perspective on the economics of basic research. Building up and maintaining this 'scientific' absorptive capacity is not easy or inexpensive to accomplish. It has major organizational consequences, as it involves hiring (top)-scientists and granting them the freedom to conduct basic research (Pavitt, 1991).

Our research has a number of limitations, which suggest fruitful directions for further research. First, our findings on the role of basic research relate to firms in the pharmaceutical industry and one should be careful to generalize our findings to firms in other sectors. The

pharmaceutical industry is exceptional with respect to the relevance of basic research for technology development activities (McMillan *et al.*, 2000; Rosenberg, 1990) and with respect to appropriability conditions due to a high efficacy of patenting (Lim, 2004). However, we suspect that our results do have relevance for firms in other science-based industries in which basic research and technology development are closely linked, such as electrical machinery/ICT and aerospace (Pavitt, 1984; Klevorick *et al.*, 1995). One difference with the ICT and aerospace sectors is that in the life sciences, technologies tend to be 'discrete', with a single patent often providing effective legal protection for a new drug. In pharmaceuticals, citation-weighted patents are therefore strongly correlated with successful drug development (Chiou *et al.*, 2017). In the ICT and aerospace sectors where technologies are 'complex', patent thickets and strategic patenting occur more frequently (Cohen *et al.*, 2000; Czarnitzki *et al.*, 2020), such that (citation-weighted) patent output may be a less powerful measure of innovation performance. It would be interesting to investigate whether the relationships between basic research and firms' innovative performance that we have uncovered hold up to scrutiny in other industries.

Second, since our analysis has shown that the role of internal basic research as direct input for technology development has increased in recent times, one could examine – given the decreasing basic research investments of firms – more in detail the enabling organizational characteristics for a close alignment between in-house basic research and technology development to occur. One way to examine these more detailed intra-organizational patterns is through case studies. Another way may be to analyse collaboration and citation patterns of corporate scientists and engineers, using, for example, information that is available in firms' patent and publication data.

Third, the partial mediation of the two mechanisms through which internal basic research improves innovation performance does suggest that there are other possible advantages of conducting basic research. Engagement in basic research may act as an admission ticket to R&D partnering with universities (Liebeskind *et al.*, 1996; Cockburn and Henderson, 1998), or as a

recruiting tool for high quality 'star' scientists (Henderson and Cockburn, 1996; Hicks, 1999). Further research could examine these additional mechanisms and their relative importance compared to the two mechanisms that were studied in this paper.

Finally, our work ties into the debate on science-based drug development: to increase the efficiency of the drug development process and to more accurately predict the chance of success before entering expensive clinical trials, in which industry experts have emphasized the importance of leaning more explicitly on scientific insights (Kola & Landis, 2004; Cook *et al.*, 2014; Hay *et al.*, 2014; Waring *et al.*, 2015; Chiou *et al.*, 2016). Most notably, mismatches between the drug compound, disease, clinical techniques and target patient group are issues that can be potentially foreseen and even resolved when drug candidates are strongly grounded in scientific research. While our paper considers patents as the outcome rather than the subsequent drug development process, such as the chance that a patented molecular compound enters clinical trials or its eventual development success, a natural extension of our analysis would be to study the relation between a patented compound's scientific origins, the firm's involvement in producing the underlying science, and its ability to build on it in technology development.

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Tables

Table 1: Summary statistics and pairwise correlations (n=793)

	Variable	Mean	St. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Innovation performance	1,019.65	1,751.40	0	15,948								
(2)	Internal basic research†	275.93	422.79	0	2,294	0.21							
(3)	Build on internal basic research†	54.56	197.53	0	2,662	0.10	0.13						
(4)	Build on external basic research†	1,742.33	3,277.92	0	33,914	0.05	0.18	0.60					
(5)	R&D	1,468,690	2,208,968	2,076	11,000,000	-0.07	0.12	0.41	0.64				
(6)	Propensity to publish	4.36	4.99	0	82	-0.10	-0.05	0.06	-0.01	0.25			
(7)	Technology diversification	-0.31	0.11	-1	-0.08	-0.03	0.04	-0.06	0.18	0.08	0.00		
(8)	Biotech focus	0.14	0.12	0	0.65	0.13	0.27	0.09	0.17	-0.15	-0.02	0.24	
(9)	R&D collaboration†	7.41	15.38	0	162.23	0.08	0.12	0.08	0.16	0.12	0.07	0.08	0.13

Table 2: Performing and Building on Basic Research: Empirical Results

	Model 1	Model 2	Model 3		
	Innovation performance	Innovation performance	a) Build on internal basic research	b) Build on external basic research	c) Innovation performance
Internal basic research		0.231***	0.198***	0.310***	0.156***
		(0.044)	(0.054)	(0.075)	(0.038)
Build on internal basic research					0.057**
					(0.026)
Build on external basic research					0.210***
					(0.038)
R&D	0.205***	0.082	-0.067	0.080	0.063
	(0.057)	(0.058)	(0.068)	(0.062)	(0.059)
Propensity to publish	-0.000	0.003	-0.015**	-0.017*	0.007
	(0.007)	(0.007)	(0.006)	(0.010)	(0.004)
Technology diversification	1.322***	1.401***	-1.701***	1.227***	1.113**
	(0.463)	(0.423)	(0.377)	(0.457)	(0.494)
Biotech focus	1.051***	0.463	2.031***	3.712***	-0.289
	(0.386)	(0.342)	(0.552)	(0.691)	(0.378)
Collaboration	0.033	0.021	-0.023	0.007	0.020
	(0.021)	(0.023)	(0.029)	(0.028)	(0.022)
Firm fixed effects	*included*	*included*	*included*	*included*	*included*
Year fixed effects	*included*	*included*	*included*	*included*	*included*
Constant	5.030***	5.463***	2.091**	2.829***	4.742***
	(0.766)	(0.754)	(1.047)	(0.862)	(0.701)
$Var(\hat{e}_{build\ on\ int.\ BR})$			0.442***		
			(0.024)		
$Var(\hat{e}_{build\ on\ ext.\ BR})$			0.319***		
			(0.028)		
$Cov(\hat{e}_{build\ on\ int.\ BR}, \hat{e}_{build\ on\ ext.\ BR})$			0.107***		
			(0.016)		
Observations	793	793	793		
Firms	50	50	50		
Log likelihood	-5,156.492	-5,134.118	-6,542.561		

and fixed effect ordinary least squares regressions (models 3a-3b).

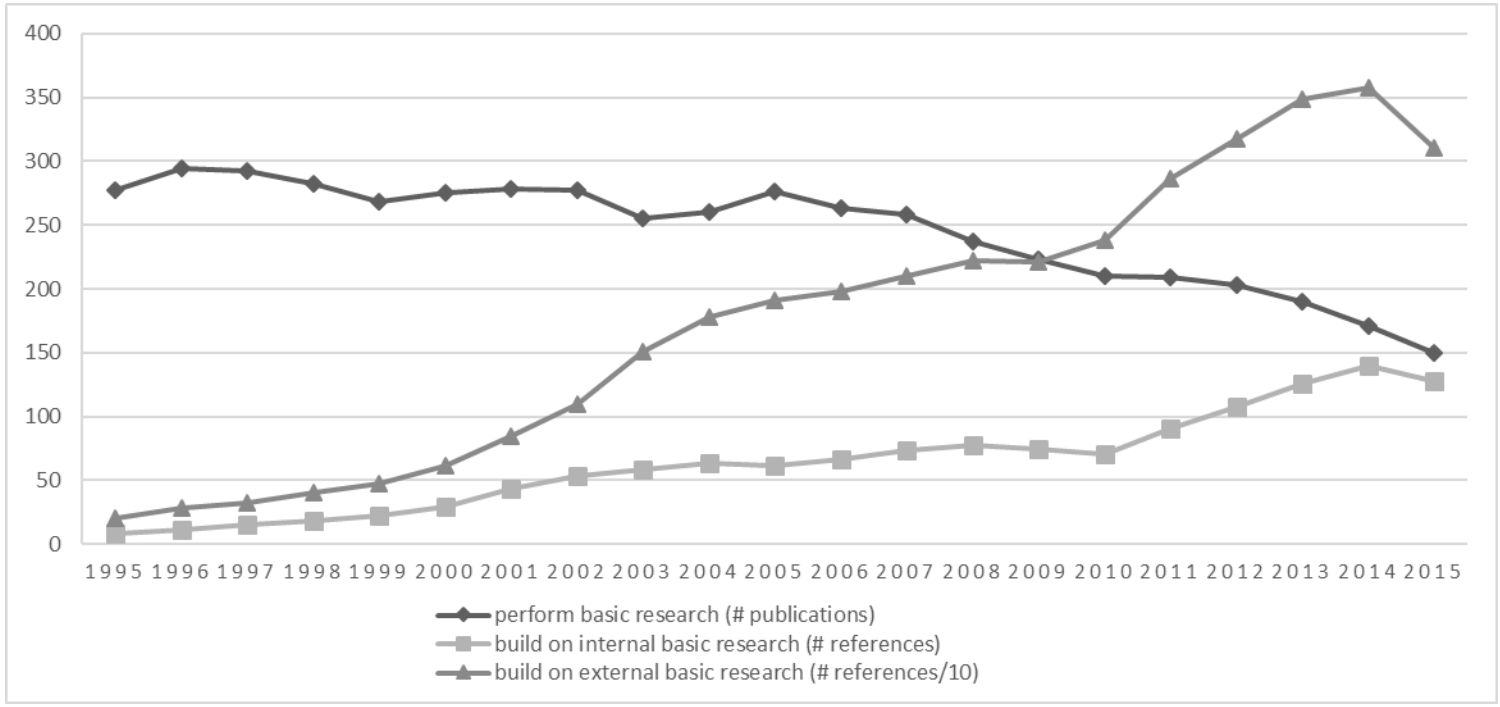
Table 3: Performing and Building on Basic Research: Comparing Periods 1 (1995-2005) and 2 (2006-2015)

	Model 1	Model 2	Model 3		
	Innovation performance	Innovation performance	a) Build on internal basic research	b) Build on external basic research	c) Innovation performance
Internal basic research - period 1		0.242***	0.157**	0.325***	0.205***
		(0.041)	(0.062)	(0.075)	(0.046)
Internal basic research - period 2		0.186***	0.329***	0.263***	0.062
		(0.041)	(0.063)	(0.071)	(0.048)
Build on internal basic research - period 1					0.056**
					(0.028)
Build on internal basic research - period 2					0.102**
					(0.047)
Build on external basic research - period 1					0.179***
					(0.045)
Build on external basic research - period 2					0.229***
					(0.051)
R&D	0.205***	0.072	-0.026	0.066	0.034
	(0.057)	(0.056)	(0.070)	(0.063)	(0.059)
Propensity to publish	-0.000	0.002	-0.014*	-0.018	0.005
	(0.007)	(0.005)	(0.008)	(0.012)	(0.005)
Technology diversification	1.322***	1.162***	-0.883**	0.935**	0.892*
	(0.463)	(0.400)	(0.438)	(0.454)	(0.455)
Biotech focus	1.051***	0.513	1.869***	3.770***	-0.133
	(0.386)	(0.344)	(0.602)	(0.651)	(0.331)
Collaboration	0.033	0.016	-0.007	0.001	0.013
	(0.021)	(0.022)	(0.033)	(0.028)	(0.023)
Firm fixed effects	*included*	*included*	*included*	*included*	*included*
Year fixed effects	*included*	*included*	*included*	*included*	*included*
Constant	5.030***	5.512***	1.831*	2.922***	4.998***
	(0.766)	(0.697)	(0.954)	(0.843)	(0.749)
$Var(\hat{e}_{build\ on\ int.\ BR})$			0.422***		
			(0.022)		
$Var(\hat{e}_{build\ on\ ext.\ BR})$			0.317***		
			(0.027)		
$Cov(\hat{e}_{build\ on\ int.\ BR}, \hat{e}_{build\ on\ ext.\ BR})$			0.114***		
			(0.015)		
Observations	793	793	793		
Firms	50	50	50		
Log likelihood	-5,156.492	-5,130.157	-6,506.007		

and fixed effect ordinary least squares regressions (models 3a-3b).

Figures

Figure 1: Time Trend of Internal basic Research and Building on Internal and External Basic Research



For expositional clarity, the variable "building on external basic research" is scaled by a factor 10.

Appendix: List of Sample Firms

Company Names	Country	Company Names	Country
Pfizer	USA	Mitsubishi Pharma	Japan
GlaxoSmithKline	UK	Shionogi	Japan
Johnson & Johnson	USA	UCB	Belgium
Aventis	France	Sepracor	USA
AstraZeneca	UK	Ono Pharmaceutical	Japan
Roche	Switzerland	Taisho Pharma	Japan
Novartis	Switzerland	Kyowa Hakko Kogyo	Japan
Merck Co	USA	Allergan	USA
Bristol Myers Squibb	USA	Ajinomoto	Japan
Eli Lilly	USA	Shire	UK
Wyeth	USA	Lundbeck	Denmark
Abbott Laboratories	USA	Tanabe Seiyaku	Japan
Schering Plough	USA	Teva Pharmaceutical Industries	Israel
Boehringer Ingelheim	Germany	Dainippon Pharmaceutical	Japan
Sanofi Synthelabo	France	Schwarz Pharma	Germany
Takeda Pharmaceuticals	Japan	Kissei Pharmaceutical	Japan
Schering	Germany	Santen Pharmaceutical	Japan
Sankyo	Japan	Watson Pharmaceuticals	USA
Merck KGAA	Germany	Ivax	USA
Yamanouchi Pharmaceutical	Japan	Mochida Pharmaceutical	Japan
Novo Nordisk AS	Denmark	Pliva	Croatia
Fujisawa Pharmaceutical	Japan	Mylan Laboratories	USA
Eisai	Japan	Recordati	Italy
Daiichi Pharmaceutical	Japan	Krka	Slovenia
Altana	Germany	Galen	UK

Notes

[1] A famous example is the development of the transistor at the Bell Telephone Laboratories in 1948 as a result of basic research activities of company scientists on the workings of semiconductor materials (Nelson, 1962).

[2] This percentage was even lower, at 3 percent, in 2006. Data on US R&D expenditures are based on tables 2-4, National Science Foundation, National Center For Science and Engineering Statistics. National Patterns of R&D Resources: 2017-2018 Data Update. NSF 20-307. Alexandria, VA. Available at https://ncses.nsf.gov/pubs/nsf20307.

[3] Two exceptions are the studies by Lim (2004) and Della Malva *et al.* (2015) who measured firms' engagement in basic research by publications in basic research journals rather than all journals.

[4] The highly skewed distribution of scientists' research output is a robust finding in the economics of science literature, starting with Lotka (1926), and has been linked to institutional factors as well as ability (Kelchtermans & Veugelers, 2012).

[5] An example of a journal that is classified in level 1 is the *Journal of the American Medical Association*. The *Journal of Biological Chemistry* is an example of a journal that is classified in level 4 (Hamilton, 2003).

[6] A value equal to one has been added before the logarithmic transformation.

[7] A similar approach to match scientific non-patent references to publications has been adopted by Marx and Fuegi (2020). While we rely on four matching parameters (journal name, volume, year, starting page), Marx and Fuegi (2020) use two additional parameters (author names, article titles).

[8] We count publications as frequently as they are cited in patents, since each citation indicates that a firm has built on science in technology development. Similar results are obtained when each cited publication is counted only once, even if its citation occurs multiple times in the 4-year patent portfolio.

[9] The ratio is set to zero if the firm had no basic research publications in the prior 4 years.

[10] As an alternative way to model overdispersion, we used a Poisson model with firm dummies and robust standard errors estimated using a quasi-maximum likelihood. This gave very similar results.

[11] The elasticity (0.011) of innovative performance to *performing basic research* mediated by *building on internal basic research* is calculated by multiplying the coefficient of *performing basic research* (0.198) in model 3 and the coefficient of *building on internal basic research* (0.057) in model 3c. A similar approach is followed to measure the elasticity (0.065) of innovative performance to *performing basic research* mediated by *external basic research* by multiplying the numbers 0.310 and 0.210.

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