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# Research versus development, external knowledge, and firm innovation

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**Abstract**

While the positive influence of external knowledge on firm innovation is widely recognized, our understanding of the interplay between the quest for external knowledge and internally conducted research and development (R&D) remains incomplete. Previous research has identified certain conditions that shape the synergy between internal and external knowledge, such as the institutional origin of the external knowledge and the overall scale of the firm's internal R&D activities. In this study, we focus on an important but not yet considered dimension and analyze whether the returns from external knowledge sourcing are contingent upon a firm's internal involvement in basic or applied *research* as opposed to *development*. We argue that engaging in research, while supporting a firm's absorptive capacity, leads overall to lower benefits from seeking external knowledge because of knowledge crowding out and spillover effects. We test our predictions using a representative panel dataset from Spain (Panel de Innovación Tecnológica [PITEC]) and show that the benefits of external knowledge decrease for higher shares of internal research investment. This substitution effect is particularly pronounced in settings where sector-level appropriability is limited and in nonhigh-tech sectors. We contribute to the innovation literature by underscoring the important role of the nature of internal R&D efforts in shaping firms' capacity to benefit from external knowledge sources.

**KEYWORDS**
absorptive capacity, corporate research, exploration, open innovation, R&D

## 1 | INTRODUCTION

A key challenge for innovative firms is whether the new technological knowledge required for product innovation should be created through internal research and development (R&D) efforts, by sourcing knowledge external to the firm, or by combining these approaches (e.g., Katila & Ahuja, 2002; Laursen & Salter, 2006). Most empirical studies have documented not only evidence of a positive impact of either activity but also a complementary relationship between them, consistent with the enabling role of absorptive capacity to benefit from external knowledge (Cassiman & Veugelers, 2006; Cohen & Levinthal, 1989; Escribano et al., 2009; Fabrizio, 2009; Lane & Lubatkin, 1998).

The complementary nature of internal knowledge production and the sourcing of external knowledge are; however, subject to boundary conditions. The extant literature shows that the innovation success from combining both activities is contingent on various dimensions. These include the institutional origin of the external knowledge (Anckaert & Peeters, 2022; Cassiman & Veugelers, 2006), the breadth of the in-sourced external knowledge (Grimpe & Kaiser, 2010; Hottenrott & Lopes-Bento, 2016), the transaction and governance modes (Fey & Birkinshaw, 2005; Grimpe & Sofka, 2016), the experience with external knowledge sourcing (Ceccagnoli et al., 2014; Hoang & Rothaermel, 2010; Love et al., 2014), the structure of intrafirm knowledge networks (Grigoriou & Rothaermel, 2017; Tortoriello, 2015), and the overall level of the firm's R&D activities (Berchicci, 2013; Hagedoorn & Wang, 2012).

In this paper, we consider a so far unexplored boundary condition in the context of external knowledge sourcing, namely the composition of a firm's internal R&D in terms of (basic and applied) research (R) as opposed to development (D).[1] Research aims at generating new knowledge and identifying new cause-and-effect relationships, whereas development aims at creating new applications that are based on established technological principles (Fleming & Sorenson, 2004; Stokes, 1997). Accordingly, research is associated with the development of breakthrough technologies and an understanding of the technological landscape (Fleming & Sorenson, 2004; Rosenberg, 1990). At the same time, the risk of project failures and appropriability challenges are more pronounced compared with development activities (Arora et al., 2018, 2021; Arrow, 1962). Given these differences, R&D may not only exhibit heterogeneity regarding expected returns but also have differential effects on the benefits and costs associated with the sourcing of external technological knowledge.

**Practitioner points**

- Managers face important trade-offs when it comes to the combination of internally created and externally sourced technological knowledge, as potential complementarities are subject to boundary conditions.
- Firms engaged in basic or applied research face greater challenges in leveraging external knowledge sources. This suggests that managers in research-active firms should thoughtfully evaluate the anticipated benefits of seeking external knowledge and explore options to mitigate the risk of unintended knowledge outflows.

On the one hand, based on an improved understanding of the technological landscape, allocating more resources to research may enhance a firm's absorptive capacity, augmenting a firm's ability to recognize the relevance of external technological solutions and internalize them (Cohen & Levinthal, 1990; Fabrizio, 2009; Fleming & Sorenson, 2004). This argument suggests a positive relationship between internally conducted research and the use of external knowledge. On the other hand, a simultaneous engagement in research and external search could create specific costs that outweigh the benefits of strengthened absorptive capacity. We propose that greater redundancies in available internal and external knowledge may emerge (referred to as "crowding out"), and the magnitude of unintended, outgoing knowledge flows to rival firms may increase (referred to as "spillovers"), which could ultimately diminish a firm's innovation performance.

We analyze this interplay of engaging in internal research and search for external knowledge on a representative sample of 18,736 firm–year observations (4469 unique firms) from Spain using Panel de Innovación Tecnológica (PITEC) data for the years 2010–2015. In contrast to many other European Community Innovation Survey (CIS) data, the Spanish version is a panel dataset based on annual surveys. Another important feature is that the PITEC database combines the typical CIS design (Laursen & Salter, 2006; Leiponen & Helfat, 2010) with the OECD-type R&D surveys. This unique combination allows for detailed analyses of the composition of firms' R&D inputs, such as the proportion of financial investments in research within R&D. With this information, we can study the extent to which firms perform research and engage in the sourcing of external knowledge, and we can examine related performance implications.

[1]The technical definitions of R and D follow the Frascati manual of the Organization for Economic Cooperation and Development (OECD), in which research is defined as "experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundations of phenomena and observable facts, without any particular application or use in view," whereas development is defined as "systematic work, drawing on knowledge gained from research and practical experience, that is directed to producing new materials, products, and devices; to installing new processes, systems, and services; or to improving substantially those already produced or installed." The latter is "directed primarily toward a specific practical aim or objective" (https://www.oecd.org/innovation/frascati-manual-2015-9789264239012-en.htm).

An important feature of this study is our focus on external knowledge sourcing in the form of *soft openness*, which describes the informal search for external knowledge without establishing contractual agreements (Laursen & Salter, 2006). For formalized R&D alliances, overestimated knowledge complementarities and the risk of unintended technology spillovers have long been recognized as a threat to alliance success (Bogers, 2011; Oxley, 1997; Oxley & Sampson, 2004; Palomeras & Wehrheim, 2020; Ritala & Hurmelinna-Laukkanen, 2013). For soft openness, however, it is less obvious whether firms experience difficulties in leveraging complementarities, as they can refocus faster to draw from alternative sources compared with contract-based alliances with fixed time horizons. Similarly, while the literature on the "paradox of openness" also suggests a spillover risk in the context of informal external knowledge sourcing despite a lower frequency of bi-directional knowledge flows compared with formal alliances (Bogers, 2011; Conti et al., 2013; Foege et al., 2019; Laursen & Salter, 2014; Ritala & Stefan, 2021), the magnitude of spillovers and the role of boundary conditions is less established.

Our empirical findings show that the positive association between external search and innovation performance is significantly lower for firms with a greater commitment to research than for firms that are not or are only marginally engaged in research. This substitution effect between activities unfolds unambiguously, with gains from external knowledge being almost three times larger for nonresearch-active firms than for research-active firms. In other words, research-active firms can only moderately enhance their innovation performance by searching in parallel for external knowledge, whereas the gains are substantial for firms that are exclusively engaged in development. We also find that this substitution effect is less pronounced for firms that are active in sectors with effective patent protection, which suggests that outgoing knowledge spillovers are an important underlying mechanism that drives our findings.

These results provide new insights for the literature on absorptive capacity, open innovation, and technology search in that they identify important contingencies. First, our findings inform a long-lasting debate on the complementarity (or substitutability) of internal and external knowledge and the enabling role of firms' absorptive capacity. A core prediction is that engaging in research, beyond engaging in development, increases firms' absorptive capacity, which would consequently increase the effectiveness of external technology sourcing (Cohen & Levinthal, 1989; Escribano et al., 2009; Fleming & Sorenson, 2004). Although our findings do not challenge the importance of absorptive capacity, a core insight of this paper is that engaging in research may come with specific challenges in the context of external knowledge sourcing. Our results suggest that for research-active firms, finding valuable external knowledge is more difficult because of knowledge crowding-out effects (Grimpe & Sofka, 2016) and more pronounced appropriability problems (Arora et al., 2021; Arrow, 1962). Therefore, for firms engaged in research, the cost of finding valuable external sources outweighs the positive effects of absorptive capacity.

Second, our study also informs the discourse on the private value of science. Some studies have shown that the private long-term payoffs from scientific research tend to be positive (Arora et al., 2021; Czarnitzki & Thorwarth, 2012; Hsu et al., 2021; Simeth & Cincera, 2016), whereas others found evidence that firms' returns from engaging in research have declined over time (Arora et al., 2018). These conclusions were predominantly drawn from large publicly listed firms in the United States. We provide an empirical contribution through a representative dataset for a major European economy, which includes both private and public firms from a large variety of sectors, thus increasing the generalizability of our findings. Our analyses support the view that scientific research allows for a premium for firm innovation performance, while parallel engagement in research and external knowledge sourcing diminishes the returns from engaging in the latter. While our study design does not allow for causal interpretations, we highlight the tensions between internal knowledge creation and external search when accounting for the different natures of firms' internal R&D.

## 2 | THEORETICAL BACKGROUND AND HYPOTHESES

In this section, we discuss the mechanisms of the effect of the relationship between internal research and search for external knowledge on innovation performance. We first present two baseline hypotheses (Hypothesis 1a and Hypothesis 1b) that revisit established findings and then theorize on the main relationship of interest (Hypothesis 2) and a boundary condition thereof (Hypothesis 3).

### 2.1 | The roles of internal research and external knowledge in firm innovation

#### 2.1.1 | Research versus development

Firms have several incentives to perform research. Actively engaging in research allows firms to obtain new insights on cause-and-effect relationships and scientific fundamentals, which may enable them to identify new technological principles for their own product development. This frequently results in first-mover advantages, as the research-active firm can translate the scientific insights into innovative products and processes ahead of its competitors (Arora et al., 2018; Nelson, 1959; Rosenberg, 1990). More broadly, research enables firms to develop new technological products that depart substantially from previous product solutions. Therefore, research-active firms frequently create radical innovations with breakthrough characteristics instead of following known technological pathways that result in small, incremental improvements (Pavitt, 1991). Conversely, development efforts build on existing knowledge and known technological principles and, consequently, primarily improve existing product solutions gradually (Czarnitzki & Thorwarth, 2012; Stokes, 1997).

Moreover, engaging in research also helps firms to obtain a sophisticated understanding of the scientific and technological landscape (Cohen & Levinthal, 1989; Fabrizio, 2009; Fleming & Sorenson, 2004; Higón, 2016). This enables them to systematically identify technological opportunities and conduct a directed, timely search for relevant knowledge inputs, thereby reducing wasteful experimentation. Relatedly, research activity increases a firm's absorptive capacity and improves its internalization of externally sourced knowledge. On the other hand, development activity may not create a similar fundamental understanding, which implies a lower ability to anticipate new technological trends. The creation of relevant scientific knowledge can also imply privileged access to academic communities and potential collaboration partners, especially if firms engage in the dissemination of research findings at academic conferences and in peer-reviewed scientific journals (Hicks, 1995; Rosenberg, 1990; Slavova, 2022).

Despite these potential advantages, engaging in research is associated with higher failure and appropriability risks than performing development (Arora et al., 2018; Arrow, 1962; Nelson, 1959). Research is inherently tied to uncertainty about outcomes, and once successful outcomes are realized, they are difficult to protect because research results may not be patentable (Arora et al., 2021; Arrow, 1962). Moreover, outcomes of research activities can typically be used for technology development in multiple product market domains, which increases the magnitude and scope of potential knowledge spillovers from research relative to those from development (Akcigit et al., 2021).

Empirical studies have found a positive association between internally conducted research and firm productivity (Czarnitzki & Thorwarth, 2012; Mansfield, 1980), revenues (Barge-Gil & Lopez, 2014; Higón, 2016), and firm value (Arora et al., 2021; Hsu et al., 2021; Simeth & Cincera, 2016), although these studies also document heterogeneity regarding sectors, time trends, and idiosyncratic firm characteristics. Studies have also shown that firms engaging in research activities obtain better innovation outcomes in terms of quantity, quality, and timing (Fabrizio, 2009; Gambardella, 1992). Based on these arguments, we hypothesize:

> **Hypothesis 1a.** Stronger engagement in internal research, relative to development, has a positive effect on firm innovation performance.

### 2.1.2 | External search

On the flip side, the costs, risks, and challenges of internal R&D activity, as well as rapidly emerging technological opportunities, incentivize companies to consider external information sources for innovation (Chesbrough, 2003; Laursen & Salter, 2006; Rosenkopf & Nerkar, 2001; Vega-Jurado et al., 2009). The growing division of labor and specialization in technology development make it difficult for firms to innovate only with internal resources (Arora et al., 2001; Jones, 2009). By relying on external sources of innovation, firms can gain access to new groundbreaking technologies, share costs and risks, and identify new opportunities for product innovation. They can leverage external knowledge through various search channels, such as formal R&D collaboration (Cassiman & Veugelers, 2002), markets for technology (Arora et al., 2001), crowdsourcing (Afuah & Tucci, 2012), informal (or soft) openness strategies (Laursen & Salter, 2014), and strategic hiring (Palomeras & Melero, 2010), all of which may help generate a competitive advantage (Dyer & Singh, 1998).

While external search is generally beneficial for innovation performance (Cassiman & Veugelers, 2002; Katila & Ahuja, 2002; Laursen & Salter, 2006), the literature also shows that external search comes at a cost, such as the risk of over-searching (Deeds & Hill, 1996; Laursen & Salter, 2006), the pursuit of self-interest at the expense of the partner (Gulati, 1995; Williamson, 1985), and the risk of knowledge leaking outside the joint project (Hottenrott & Lopes-Bento, 2015; Kesteloot & Veugelers, 1995). Several studies have shown that excessive use of external knowledge is associated with diminishing returns, as there is a point at which costs outweigh benefits (Hottenrott & Lopes-Bento, 2016; Laursen & Salter, 2006). The process of learning to absorb external knowledge is linked to high uncertainty, as knowing ex ante which external sources are worth pursuing is difficult for managers. Therefore, heavy reliance on external knowledge puts high demands on firms' selection and integration capabilities, and orchestrating multiple sources of external knowledge simultaneously may become increasingly complex (Laursen & Salter, 2006).

Typically, these costs are explained by transaction cost economics, which relates firms' boundaries to their need to internalize what is difficult or costly to find in the market, or what is vulnerable to opportunistic behavior in the market (Argyres & Zenger, 2012; Williamson, 1985). As these costs likely escalate for firms that conduct research—and in line with previous findings and theoretical considerations—we expect a positive but nonlinear relationship between the use of external knowledge and firms' innovation:

> **Hypothesis 1b.** Stronger engagement in external knowledge sourcing has a positive effect on firm innovation performance, but with diminishing returns.

## 2.2 | The relationship between internal research and external knowledge for firm innovation

Engaging in scientific research helps firms to build internal knowledge, enabling them to identify and absorb external knowledge that could prove useful for their R&D activities (Cockburn & Henderson, 1998; Dyer & Singh, 1998; Lane & Lubatkin, 1998). As discussed in Section 2.1.1, better understanding of the scientific and technological landscape permits firms to identify relevant external technologies for their own innovation activities more easily (Fabrizio, 2009; Fleming & Sorenson, 2004). The positive role of engaging in research in the expansion of a firm's absorptive capacity may prove particularly useful in the context of informal sourcing of external knowledge, which typically involves fewer interpersonal interactions with external partners. The absence of formalized exchanges implies that external knowledge will be largely tacit, which requires the absorbing firm to have a deeper understanding of scientific and technological fundamentals (Cowan & Foray, 1997; Grimpe & Sofka, 2016). However, contrary to development, performing research could also lead to diminishing returns of external knowledge sourcing because of knowledge crowding out effects and increasing knowledge spillovers.

Regarding crowding-out effects, firms that are active in conducting research are closer to the knowledge frontier compared with firms that primarily invest in development. The generated scientific knowledge stemming from the research activities may consequently reduce the added value of externally available knowledge. Research generates new insights on unknown cause-and-effect relationships between distinctive knowledge elements, and therefore advances the state-of-the art (Rosenberg, 1990). These new insights may then allow for the development of superior technologies that are central for introducing new innovations. However, when a firm is close to the scientific frontier, many potential sources of external knowledge may not provide complementary insights that go beyond what is known to the firm already based on its own research. Even if a research-active firm still experiences the need to find complementary external knowledge and technologies, this may prove more difficult because the required inputs may not yet exist in a form that will be useful to the firm (Grimpe & Sofka, 2016). Therefore, a research-active firm might be required to consider a greater number of external sources to increase the probability of finding knowledge that is not yet available internally and which substantially enhances a firm's product development efforts. Ultimately, search costs increase because of broader and more intensive screening efforts (Grigoriou & Rothaermel, 2017; Grimpe & Kaiser, 2010; Laursen & Salter, 2006).

A second mechanism refers to increasing knowledge spillovers. External knowledge sourcing may become particularly problematic in terms of spillover risks when a firm engages in research, since research results are more generic than development results regarding potential product market applications (Akcigit et al., 2021; Arora et al., 2021) and given the greater difficulties in protecting research results using legal intellectual property rights, such as patents (Arrow, 1962). In terms of concrete channels, spillovers may occur through various channels, such as through researcher mobility to other firms, codified outputs via scientific publications, or exchanges at conference presentations (Arora et al., 2021; Stern, 2004). Importantly, when firms engage in external search for knowledge, a certain degree of interaction with other organizations will occur, since firms need to go beyond passive desk research, irrespective of the contractual nature of an agreement (Laursen & Salter, 2014). It follows that engaging in external search may divulge broader research agendas to outsiders and thereby endanger firms' strategic and innovation moves. This may cause external search benefits to be overshadowed by spillovers and free riding by competing firms (Lieberman & Montgomery, 1988). Put differently, even if the producing firm can translate the research findings into its own products, other firms could derive innovative products or equally successful substitutes based on spillovers originating from internal research (Giarratana & Mariani, 2014; Grimpe & Sofka, 2016; Laursen & Salter, 2014; Lim, 2009).

> **Hypothesis 2.** The stronger the engagement in internal research, relative to development, the weaker the gains from external knowledge sourcing for firm innovation performance.

### 2.3 | Sector-level appropriability conditions

As discussed in the previous section, a core mechanism of the interplay between research and the use of external knowledge involves outgoing knowledge spillovers. Indeed, simultaneously engaging in external knowledge sourcing and the associated interactions with the environment may prove harmful to the research-active firm (Giarratana & Mariani, 2014) because the outcomes of research are difficult to protect (Arora et al., 2021; Arrow, 1962; Nelson, 1959). Importantly, however, the risk of knowledge spillovers and their competitive implications are unlikely to be uniform across industrial sectors (Laursen & Salter, 2014). The outcomes of research can be better protected in some industries than in others (Cohen et al., 2000; Levin et al., 1987). If patents secure inventions and related innovative products from competition, the negative implications of knowledge outflows in the context of firms' search activities are likely to be less significant. Scientists can more openly interact with external actors if the recipient firm cannot use the knowledge easily without infringing on other firms' patents (Palomeras & Wehrheim, 2020).

A prime example of strong appropriability conditions is the life sciences industry, in which new research findings result simultaneously in scientific publications and patents (Gans et al., 2017; Murray, 2002). While the external search process may provide information on firms' research findings to rival firms, commercially viable parts of the output can be protected at least partially with a patent that covers claims regarding the application of the knowledge. In many other sectors, however, protecting early-stage research with patents is somewhat challenging. In line with this view, Laursen and Salter (2014) show that firms increase the breadth of their external search depending on the strength of appropriability conditions. Consistent with previous findings, we expect the spillover risks from internally conducted research and external knowledge sourcing to be sector-dependent, with lower spillover risks in patent-intensive sectors than in other sectors.

> **Hypothesis 3.** The substitution effect between internal research and external knowledge sourcing is less pronounced for firms that benefit from stronger sector-level appropriability.

## 3 | DATA AND METHODOLOGY

### 3.1 | Dataset and variables

For our empirical analysis, we use data from PITEC. The survey is administered annually by the National Statistics Office of Spain (Instituto Nacional de Estadistica) in collaboration with the Spanish Science Foundation (FECYT), and the resulting dataset is a combination of standardized data from the European CIS and the R&D surveys based on the Frascati and Oslo Manuals.[2] The PITEC survey is a well-established and popular data source for studies on firm innovation (for recent examples, see Gomez et al., 2020; Martínez-Noya & García-Canal, 2021) due to the comprehensiveness of the available information and its structure as an annual panel. The survey exhaustively targets (1) all firms with 200 or more employees (regardless of whether or not they are engaged in R&D), (2) all firms with <200 employees that spend on R&D, and (3) a representative (i.e., nonexhaustive) sample of firms with <200 employees that do not conduct any R&D activity (Gomez et al., 2020). The PITEC survey is also characterized by very high response rates, varying between 92% and 96% (FECYT, 2016), thus allowing for a nearly exhaustive representation of the innovation activities of the private sector in Spain. Due to such comprehensive and fine-grained information on R&D and innovation activities at the firm level, the survey's Spanish microdata have been frequently used in various innovation studies (Beneito, 2003; Bianchi et al., 2014; Kotlar et al., 2013; Llopis & D'Este, 2022; Sikimic et al., 2016; Un, 2015).

The data used for our analysis span 2010–2015 and comprise 18,736 firm–year observations (involving 4469 firms).[3] As Spain faced severe disruptions to its economy during the 2008 financial crisis, we focus on post-crisis years, starting with the year 2010. The sample is limited to R&D performing companies in the manufacturing and knowledge-intensive service sectors, as the types of R&D activities differ considerably in other service sectors.[4,5] We

[2]Oslo Manual: https://www.oecd.org/science/oslo-manual-2018-9789264304604-en.htm. See above footnote 1 for the link to the complementary Frascati Manual.

[3]Similar to other national versions of the CIS innovation survey, the Spanish PITEC survey is at the level of the firm (as opposed to the higher consolidated corporate group level or the lower branch level).

[4]See also Barge-Gil and Lopez (2014) for a similar application of the Spanish PITEC dataset.

[5]In the last year of our sample period (2015), Spain's business R&D expenditures amounted to 6.9 billion EUR, which translates into 10.4 billion USD when standardized purchasing power parity prices of 2015 are applied. Therefore, the overall size of business R&D activity in Spain is comparable to that of Israel (10.8 billion USD), Sweden (10.8 billion USD), Switzerland (11.2 billion USD), and Australia (11.3 billion USD). In the manufacturing sector, the industries with the largest R&D spending are motor vehicles and transport equipment (916 million EUR), pharmaceuticals and chemicals (823 million EUR), aircraft (397 million EUR), machinery (222 million EUR), and manufacturing of electrical equipment (212 million EUR). In the service sector, R&D services (1.54 billion EUR) and information and communication services (795 million EUR) are notable in terms of business R&D spending.

**TABLE 1** Variable descriptions.

| Variable name | Description |
|---|---|
| *Dependent variables* | |
| INNO | Share of revenues from innovative products or services in year $t$ on all revenues of the firm $i$ in year $t$. Innovative products or services are defined as those that were introduced to the market between year $t$ and year $t-2$ |
| LOG PATENTS | Natural logarithm of the number of new patents filed by the firm $i$ at the Spanish Patent and Trademark Office (OEPM) in year $t$ |
| PRODUCT | Dummy variable if firm $i$ introduced a new product or service in year $t$ |
| *Independent Variables* | |
| SHARE RESEARCH | Share of expenditures devoted to basic and applied research ("R") as ratio on total R&D expenditures of firm $i$ in year $t$ |
| SEARCH BREADTH | No. of external source types of knowledge for innovating that are at least of medium importance for firm $i$ in year $t$ |
| *Control variables* | |
| R&D INTENSITY | Share of R&D expenditures as ratio to revenues by firm $i$ in year $t$ |
| FIRM SIZE | Firm size as measured by the number of employees (in logs) |
| PUBLIC FUNDING | Dummy variable if firm $i$ receives public R&D funding in year $t$ |
| COLLABORATION | Dummy variable if firm $i$ engages in an innovation-related collaboration with another organization in year $t$ |
| EXPORT | Share of revenues by firm $i$ in year $t$ that originate from export activity |
| START-UP | Firm $i$ is younger than 5 years in year $t$ since its inception |
| SCIENCE PARK | Firm $i$ is located in a science or technology park in year $t$ |
| BUSINESS GROUP | Firm $i$ is not independent and belongs to a business group in year $t$ |
| PATENT | Firm $i$ relies on patents as an appropriability instrument in year $t$ |
| TRADEMARK | Firm $i$ relies on trademarks as an appropriability instrument in year $t$ |
| LABOR PRODUCTIVITY | Revenues divided by the number of employees (firm $i$ in year $t$) |
| *Additional variables used in complementary tests* | |
| LOG RESEARCH | Nat. logarithm of financial investments in research ("R") by firm $i$ in year $t$ |
| LOG DEVELOPMENT | Nat. logarithm of financial investments in development ("D") by firm $i$ in year $t$ |
| SEARCH BREADTH LS2006 | No. of external source types of knowledge for innovating that are at least of low importance (as opposed to no importance) to firm $i$ in year $t$ |
| SEARCH BREADTH HIGH | No. of external source types of knowledge for innovating that are of high importance to firm $i$ in year $t$ |
| COLLABORATION BREADTH | No. of external R&D collaboration partner types for which firm $i$ has entered collaboration agreements in year $t$ |
| SHARE PAT SECTOR | Sector-level ($j$) use of patenting as appropriation instrument (no. of firms patenting divided by the number of all firms in sector) |

Abbreviation: R&D, research and development.

exclude firms with fewer than 10 employees and impose a minimum sales amount of 500,000 EUR.

We analyze the relationship between the firms' internal *research* and their use of external knowledge sources on the firms' innovation performance. By construction, internally conducted *development* is the reference category throughout our analyses. The complete list of variables used in the analysis is provided in Table 1. We measure firm innovation performance (*INNO*) by using a well-established variable, which is the share of revenues of firm $i$ in year $t$ that originate from innovative products and services in relation to total revenues. Products and services are considered to be innovative if they were introduced to the market in year $t$ or the previous 2 years ($t-1$ and $t-2$). In other words, products and services are considered innovative if their introduction has taken place any time between $t-2$ and $t$, while the corresponding revenues are available on an annual basis (year $t$).

This reflects the standard design in all CIS surveys (Klingebiel & Adner, 2014; Laursen & Salter, 2006; Leiponen & Helfat, 2010). We do not distinguish between innovative products and services that are new to the market and those that are only new to the firm, as long as a product or service complies with the basic definition of an innovation.[6] The dependent variable varies continuously between 0 (none of the firms' revenues are based on innovative products) and 1 (all of the firms' revenues are derived from innovative products), and is both left and right censored. In untabulated tests of robustness, we also translate this outcome measure into the absolute (log-transformed) revenue amount, which delivers identical results.

Several measures among the independent variables are related to the firms' search and internal R&D activities. We follow the prior literature and measure the breadth of the firms' external knowledge sourcing through the number of external sources exploited to gather information for innovation.[7] In line with Laursen and Salter (2006, 2014), *SEARCH BREADTH* counts the number of unique sources in terms of universities, public research institutes, suppliers, users, competitors, technology centers, and private R&D labs or consultants, and therefore the measure varies between 0 and 7. Like Laursen and Salter (2014), we do not include conferences, scientific journals, or professional associations because these external search channels can be regarded as passive and could overlap with the other sources included in our main measure. For example, a firm may source knowledge from universities or other firms while attending a scientific conference. Moreover, we consider a particular source only if it is considered at least of medium importance to the firm, in line with the operationalization by Laursen and Salter (2014). To ensure that our results are not driven by arbitrary definitions of our search measure, we also apply the original *SEARCH BREADTH* measure of Laursen and Salter (2006) in a robustness test (that counts all sources if they are of low, medium, or high importance; as opposed to being of no importance) and an additional variation in which we consider only sources of high importance. The empirical analysis leads to identical conclusions, regardless of these variations in the operationalization of the measure.

The second independent variable of interest is related to firms' research. We measure the extent of a firm's research activities by computing the share of a firm's overall R&D expenditure in each year $t$ that is spent on research, as opposed to development (*SHARE RESEARCH*). Similar to the dependent variables, this variable is scaled between 0 (the firm conducts no research) and 1 (the firm conducts only research and no development). To assess the variable's robustness, we also introduce R&D in levels for research and development as two continuous (log-transformed) measures and replicate our main regressions, with similar findings.

We include several other factors that can influence a firm's innovation performance. Of these, we include the firm's R&D intensity (*R&D INTENSITY*), which reflects its investment in internal R&D relative to its revenue. We also control for the firm size as measured by the (log-transformed) number of employees (*FIRM SIZE*); the ownership status—that is, whether the firm belongs to another firm (*BUSINESS GROUP*); the firm's export share with regard to its revenue (*EXPORT SHARE*) because internationalization and innovation activities are related; whether the firm has benefitted from public subsidies (*PUBLIC FUNDING*); whether the firm is located in a science or technology park (*SCIENCE PARK*); whether the firm is a start-up firm younger than 5 years (*START-UP*); whether the firm is engaged in a formal R&D collaboration (*COLLABORATION*); and whether the firm relies on patents (*PATENT*) or trademarks (*TRADEMARK*) to appropriate returns from innovations. As the decision to engage in an external search might be contingent on the firm's performance and quality, we follow Laursen and Salter (2014) and include a variable that accounts for labor productivity (*LABOR PRODUCTIVITY*). Finally, we include 25 industry dummies at the NACE two-digit level to control for any remaining industry effects, and six-year dummies to account for general time trends.

## 3.2 | Descriptive statistics

Table 2 presents the descriptive statistics of the dependent and independent variables used in the analysis.[8] As Table 2 presents, an average of 29% of the sales of the firms in our sample stems from innovative products, and

[6]Innovations comprise products and services that are new or significantly improved with regard to basic functionalities, technical specifications, incorporated software or other intangible components, and performance. The survey provides a detailed list of examples and nonexamples to respondents and explicit definitions based on the Oslo Manual of the OECD. Therefore, the residual (noninnovative) revenue either comes from products and services that do not comply with this definition of an innovation or from products and services that did constitute innovations at their time of market introduction but were introduced before the year $t-2$.

[7]The survey asks respondents to indicate the importance of various listed information sources for firms' innovation activities. The instructions further state that this may refer both to information used for new innovation projects and information that contributed to the completion of ongoing innovation projects during the survey period. The importance is captured by a 4-point Likert scale, consisting of *no use*, *low use*, *medium use*, and *high use*.

[8]See Table A1 for a complementary correlation matrix.

**TABLE 2** Descriptive statistics.

| | Mean | SD | Median | Min | Max |
|---|---|---|---|---|---|
| INNO | 0.29 | 0.36 | 0.10 | 0.00 | 1.00 |
| SHARE RESEARCH | 0.39 | 0.41 | 0.25 | 0.00 | 1.00 |
| SEARCH BREADTH | 3.16 | 2.01 | 3.00 | 0.00 | 7.00 |
| R&D INTENSITY | 0.09 | 0.36 | 0.02 | 0.00 | 12.09 |
| FIRM SIZE | 225.90 | 633.75 | 73.00 | 10.00 | 9673.00 |
| PUBLIC FUNDING | 0.63 | 0.48 | 1.00 | 0.00 | 1.00 |
| COLLABORATION | 0.43 | 0.49 | 0.00 | 0.00 | 1.00 |
| EXPORT | 0.14 | 0.20 | 0.04 | 0.00 | 1.00 |
| START-UP | 0.00 | 0.05 | 0.00 | 0.00 | 1.00 |
| SCIENCE PARK | 0.06 | 0.25 | 0.00 | 0.00 | 1.00 |
| BUSINESS GROUP | 0.51 | 0.50 | 1.00 | 0.00 | 1.00 |
| PATENT | 0.18 | 0.38 | 0.00 | 0.00 | 1.00 |
| TRADEMARK | 0.22 | 0.41 | 0.00 | 0.00 | 1.00 |
| LABOR PRODUCTIVITY | 0.25 | 0.44 | 0.17 | 0.00 | 15.80 |
| *Additional variables* (*complementary analysis*) | | | | | |
| LOG PATENTS | 0.15 | 0.47 | 0.00 | 0.00 | 6.33 |
| PRODUCT | 0.81 | 0.39 | 1.00 | 0.00 | 1.00 |
| LOG RESEARCH | 7.05 | 6.17 | 10.52 | 0.00 | 18.49 |
| LOG DEVELOPMENT | 8.07 | 6.00 | 11.22 | 0.00 | 19.32 |
| SEARCH BREADTH LS2006 | 4.86 | 2.17 | 5.00 | 0.00 | 7.00 |
| SEARCH BREADTH HIGH | 1.21 | 1.38 | 1.00 | 0.00 | 7.00 |
| COLLABORATION BREADTH | 1.19 | 1.80 | 0.00 | 0.00 | 7.00 |
| SHARE PAT SECTOR | 0.17 | 0.11 | 0.14 | 0.00 | 1.00 |

*Note*: $N = 18{,}736$ firm-year observations.

the firms source knowledge from an average of 3.16 source types, which confirms the importance of external inputs in a firm's innovation activities and demonstrates that many firms screen several sources simultaneously. Figure 1 shows the development of the firms' search activities over time in the four selected R&D-intensive sectors. The figure reveals that the use of external knowledge sources remained largely stable over the study period, and the level of simultaneously used external sources was sector-dependent, with the lowest number of external sources being in the automotive sector (between 2 and 3 throughout the sample period), and the highest in R&D services (between 4.5 and 5 throughout the sample period).

Table 2 further presents that the average share of internal R&D devoted to research is 39%. Figure 2 depicts the same selection of industries as in Figure 1 but plots the budget invested in research. As is the case for external sources, the figure shows a certain level of stability in research investment over time. Decomposed by sector, the data show that pharmaceuticals and R&D services have the highest investment shares, with ∼60% of their R&D budgets going to research, whereas the automotive sector has the lowest share, with only 30% of its R&D budget directed toward research. These numbers show that while many firms engage in both activities, several sector-level specificities are likely to be associated with heterogeneity in innovation performance. This observation reinforces the need to consider both research and external search jointly as well as across different sectors.

The average firm size in our sample is 226 employees (with a median of 73). Approximately 60% of the firms receive some type of public support, and around half belong to a business group. Moreover, 40% have at least one formal collaboration, and about 14% are active exporters. Slightly <20% use patent protection, whereas slightly more than 20% use trademarks.

Figure 3 displays *SEARCH BREADTH* depending on different levels of internally conducted research. Firms with no research have an average *SEARCH BREADTH* of 2.75 sources; with a research share lower than 25% (of its total internal R&D budget), 3.61 sources; with a research share of 25%–50%, 3.91 sources; with a research share of 50%–75%, 3.67 sources; and with a research share of 75% or more, 3.00 sources.

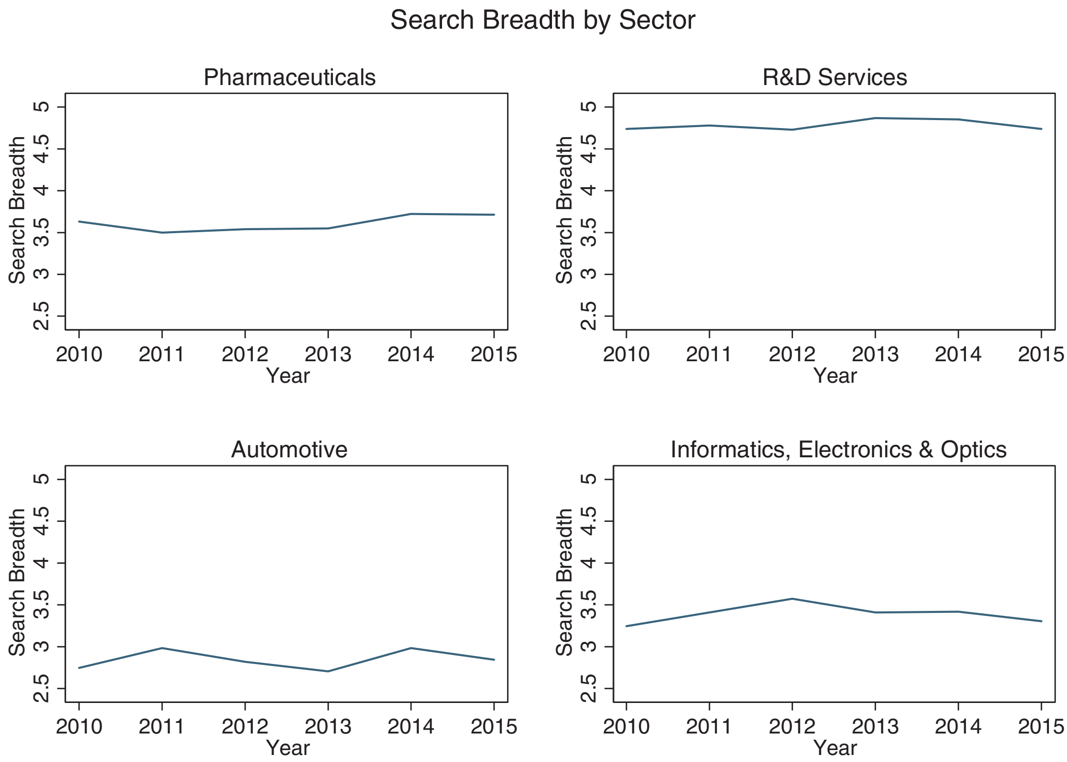


**FIGURE 1** Firms' engagement in external search (selected sectors). R&D, research and development.

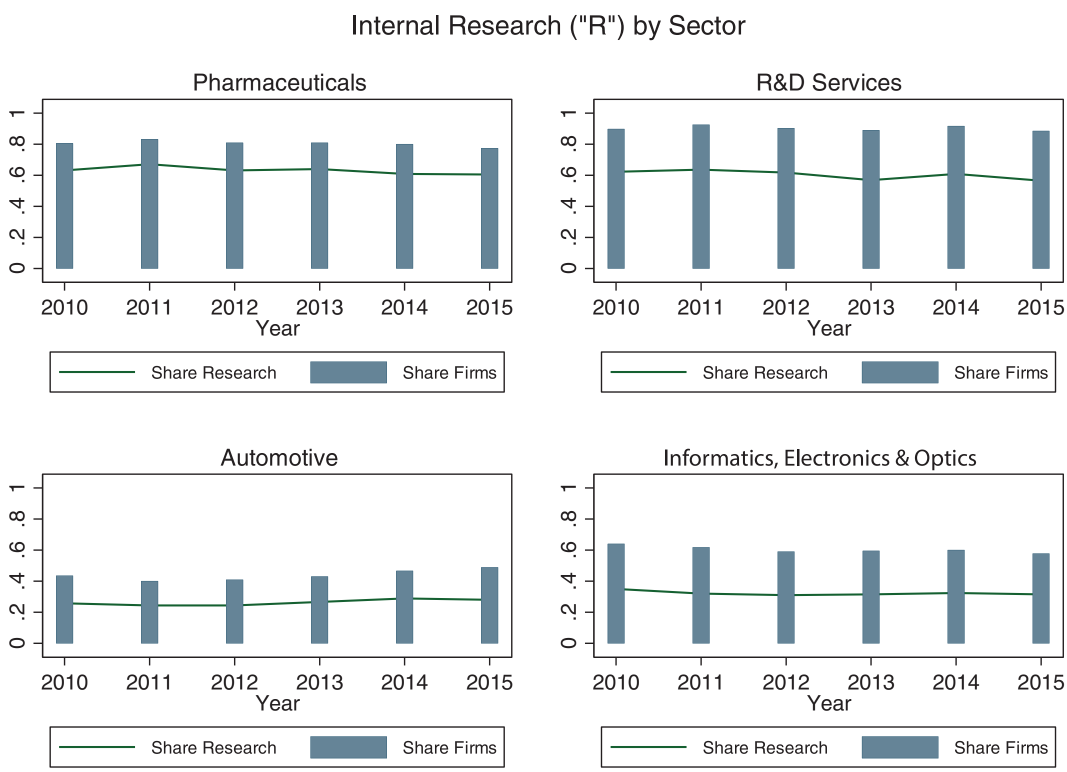


**FIGURE 2** Firms' engagement in internal research (selected sectors). R&D, research and development.

Therefore, without holding other characteristics constant, we observe a complementarity between internal research and external search until about 50% of the R&D are devoted to research, before *SEARCH BREADTH* begins to slightly diminish with larger shares of research.

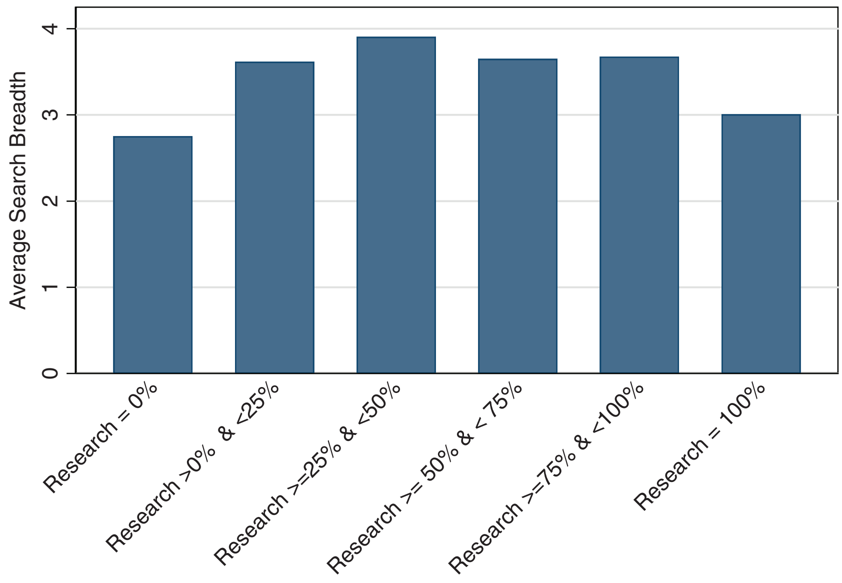


FIGURE 3 *SEARCH BREADTH* conditional on *SHARE RESEARCH*.

## 3.3 | Econometric model

We use Tobit regression models as our main specification to account for the censored nature of the dependent variables. Because we use panel data, we cluster standard errors by firm in all our models. Achieving consistent estimates in Tobit models is not possible when firm fixed effects are used (e.g., Czarnitzki & Toole, 2011), and our main independent variables, particularly the research-related measures, are fairly stable over time. This leads to insufficient variation in our time series (Belderbos et al., 2012), so we do not use firm fixed effects in our main specifications (Hall et al., 2005). Consequently, we only use firm fixed effects in ordinary least squares (OLS) regressions to test the robustness of our main findings. Our baseline specification can be represented as follows:

$$INNO_{it} = SHARE\ RESEARCH_{it} + SEARCH\ BREADTH_{it} + SEARCH\ BREADTH_{it}^2 + Z_{it} + e_{it} \quad (1)$$

where the vector $Z_{it}$ represents the standard set of control variables described in the previous section, and $e_{it}$ is the error term. To determine whether the heterogeneous effect of external search depends on firms' engagement in research, as Hypothesis 3 states, we introduce interaction terms between the measures *SHARE RESEARCH* and *SEARCH BREADTH*.[9] Holding a firm's R&D intensity constant, the interaction captures whether a firm's engagement in internal research increases or decreases the effect of its external search on its innovation performance. In formal terms, we use the following equation to assess a firm's innovation performance, considering the relationship between research and external knowledge:

$$INNO_{it} = SHARE\ RESEARCH_{it} + SEARCH\ BREADTH_{it} + SEARCH\ BREADTH_{it}^2 + SHARE\ RESEARCH_{it} \times SEARCH\ BREADTH_{it} + Z_{it} + e_{it} \quad (2)$$

# 4 | EMPIRICAL RESULTS

## 4.1 | Internal research and external knowledge sourcing for innovation

Table 3 presents the main regression results. We estimate the impact of search strategies on innovation performance depending on a firm's internal research and external search activities. Model 1 is the baseline regression, as formulated in Equation (1), which includes all variables of interest without the interaction term. We find a positive and significant effect of research intensity (*SHARE RESEARCH*), which indicates that investing in research, relative to development, has on average a positive impact on firm innovation performance. More precisely, a shift in the share of research from 0% to 100% increases the share of sales that stems from innovative

[9]This also includes the squared terms of *SEARCH BREADTH* to consider nonlinearities in the relationship between search and innovation performance (Laursen & Salter, 2006).

**TABLE 3** Internal research and external search for innovation.

| Variables | (1) INNO TOBIT Coeff. (SE) | (2) INNO TOBIT Coeff. (SE) | (3) INNO OLS Coeff. (SE) | (4) INNO OLS (FE) Coeff. (SE) | (5) INNO RE-TOBIT Coeff. (SE) |
|---|---|---|---|---|---|
| SHARE RESEARCH | 0.050*** (0.016) | 0.130*** (0.029) | 0.080*** (0.016) | 0.058*** (0.018) | 0.116*** (0.021) |
| SEARCH BREADTH | 0.039*** (0.011) | 0.047*** (0.011) | 0.012* (0.006) | 0.001 (0.007) | 0.028*** (0.008) |
| SEARCH BREADTH sq. | −0.003* (0.001) | −0.002 (0.001) | 0.001 (0.001) | 0.001 (0.001) | −0.001 (0.001) |
| SHARE RESEARCH × SEARCH BREADTH | | −0.027*** (0.008) | −0.016*** (0.005) | −0.011** (0.005) | −0.021*** (0.005) |
| R&D INTENSITY | 0.057 (0.045) | 0.058 (0.044) | 0.040 (0.025) | 0.036* (0.021) | 0.058*** (0.019) |
| FIRM SIZE | 0.009 (0.007) | 0.009 (0.007) | 0.003 (0.004) | −0.015 (0.018) | 0.008 (0.006) |
| PUBLIC FUNDING | −0.034** (0.013) | −0.033** (0.013) | −0.018** (0.008) | −0.003 (0.008) | −0.009 (0.010) |
| COLLABORATION | 0.047*** (0.013) | 0.046*** (0.013) | 0.017** (0.008) | 0.028*** (0.009) | 0.056*** (0.010) |
| EXPORT | 0.034 (0.034) | 0.031 (0.034) | 0.033 (0.021) | 0.001 (0.028) | 0.017 (0.029) |
| START-UP | −0.078 (0.119) | −0.087 (0.120) | −0.024 (0.064) | −0.134 (0.087) | −0.173* (0.090) |
| SCIENCE PARK | −0.003 (0.027) | −0.004 (0.027) | 0.006 (0.017) | −0.022 (0.041) | −0.009 (0.028) |
| BUSINESS GROUP | −0.006 (0.016) | −0.006 (0.016) | −0.005 (0.010) | −0.013 (0.019) | −0.001 (0.014) |
| PATENT | 0.072*** (0.016) | 0.073*** (0.016) | 0.038*** (0.010) | 0.024** (0.011) | 0.067*** (0.013) |
| TRADEMARK | 0.035*** (0.013) | 0.035*** (0.013) | 0.007 (0.009) | −0.016* (0.009) | −0.000 (0.011) |
| LABOR PRODUCTIVITY | 0.000 (0.000) | 0.001 (0.032) | 0.006 (0.015) | 0.040 (0.026) | 0.004 (0.016) |
| CONSTANT | 0.105* (0.061) | 0.086 (0.061) | 0.268*** (0.037) | 0.228 (0.240) | 0.109** (0.048) |
| FIRM FE | NO | NO | NO | YES | NO |
| INDUSTRY FE | YES | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES | YES |
| Observations | 18,736 | 18,736 | 18,736 | 18,736 | 18,736 |
| Firm-ID's | 4469 | 4469 | 4469 | 4469 | 4469 |

*Note*: The table shows the results of the main regression analysis. Model (1) represents a baseline Tobit model without interaction effects, Models (2)–(5) contain the interaction effect between the variables of interest *SHARE RESEARCH* and *SEARCH BREADTH*. Model (2) is estimated using a Tobit estimator and represents our preferred specification. Models (3) and (4) are OLS regressions without and with firm fixed effects, and model (6) is estimated using a Random-Effects Tobit estimator. Standard errors are clustered by firm (in parentheses).
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

products by 5 percentage points.[10] As this measure is a share of research ("R") expenditures to the total R&D expenditures, development ("D") serves as a reference category throughout the estimations, and the results pertaining to research should be interpreted relative to development. Therefore, our first baseline hypothesis, Hypothesis 1a, finds empirical support.

Similarly, in line with previous research, *SEARCH BREADTH* has a strong positive effect on innovation performance both in terms of statistical significance and effect magnitude (e.g., Laursen & Salter, 2006). However, we only find weak evidence for diminishing returns. The squared term of the search breadth measure is only significant at

[10]Tables A2 and A3 present the detailed results of the predictive marginal changes for the share of research as a percentage of the total R&D expenditures (ranging from 0% to 100%) and, equivalently, for the predictive marginal changes in *SEARCH BREADTH*.

the 10% level in Column (1), while the statistical significance disappears in the other model specifications.[11] Therefore, our Hypothesis 1b is partially supported.

Model 2 includes the interaction between a firm's external search and its research activities. Whereas *SHARE RESEARCH* and *SEARCH BREADTH* remain individually positive and significant, we find a significant negative interaction between the two variables. Thus, our core hypothesis, Hypothesis 2, is supported, suggesting that while research is beneficial for firms' innovation activities, it is not associated with notable complementarity effects with external knowledge for firms' innovation performance.

In other words, on average, performing research reduces the additional value of leveraging external sources for innovation success. At the mean value of 3.16 information sources, an increase in *SEARCH BREADTH* by one source leads to an increase in innovation performance of 3.1 percentage points for firms that do not conduct research. For firms that carry out research, this increase is only 2.5 percentage points at the sample median (i.e., 25% of the research investment in the overall R&D budget) and 1.1 percentage points for firms in the 75th percentile (i.e., a share of research of 80% within the overall R&D budget; see Table A3 for a representation of the predictive margins of *SEARCH BREADTH*). It follows that we find a clear substitution effect between the two activities, confirming that firms with high research capabilities generate less value from sourcing external knowledge.[12]

Figure 4 provides a graphical representation of this finding, confirming that the curve for *SEARCH BREADTH* is considerably flatter for firms with research activities than for firms that do not undertake research. It can also be seen that on average, firms not engaging in research need at least four external knowledge sources for their innovation performance to not differ significantly from that of firms that engage in research when these do not engage in external search. Therefore, we observe a clear substitution effect between these strategies. This finding suggests that internal research is a strategic substitute for external search strategies.

Finally, Models 3 and 4 replicate the analysis reported in Model 2 by using an OLS estimator with and without firm fixed effects. The interaction between *SHARE RESEARCH* and *SEARCH BREADTH* remains negative and statistically significant, further confirming our main findings and supporting Hypothesis 2. Finally, in Model 5, we provide the estimates of a random-effects Tobit estimator, with similar results. In all the models, the control variables have the expected signs and magnitudes.

## 4.2 | Moderating role of appropriability conditions

In Hypothesis 3, we propose that the substitution effect between internally conducted research and external search is less pronounced in settings where the spillover risks are inherently smaller. Therefore, this hypothesis is explicitly related to one of the underlying mechanisms of the lower returns of external search for research-active firms. For this analysis, we construct subsamples based on the sector-level use of patents as measures of appropriability.

We use a survey question that asks firms whether they rely on legal tools to appropriate returns from their innovations in two ways. First, we measure industry-level averages on the use of patents as an appropriation tool by aggregating this information at the sector level and then dividing the sample into industries with a high propensity to patent and industries with a low propensity to patent, based on the median value of the industry share in patent use.[13] We split samples to determine whether firms in industries that rely on strong patent protection suffer less from knowledge spillovers than firms in industries where patent protection is weak (as reflected by their lower use). Second, we use the same survey question at the firm level to make subsample regressions based on whether a given firm uses patents as appropriation tool. However, this variation serves only as a complementary test, as the first specification is preferable because sector-level information is less sensitive to endogenous firm-level choices regarding intellectual property rights. Table 4 presents the results of our analysis.

Whereas the interaction effect of interest is not statistically significant in the subsample of industries in which patents are heavily used as appropriation mechanism (Column 1), the interaction is negative and statistically

[11]Table A2 presents the detailed results of the predictive margins related to *SEARCH BREADTH* (ranging from 0 to 7). A change from no external source to one source type increases innovation performance by 4 percentage points, and a radical shift from a closed approach to an open strategy with the maximum of seven types of sources would imply an increase of almost 15 percentage points. The marginal effect of every additional source type is only slightly decreasing, and accordingly, the estimated inflection point is out of the data range with about 7.3 source types.

[12]As we do not introduce a three-way interaction term, which would allow for heterogeneous nonlinearity of *SEARCH BREADTH* by firms that engage in research and those that do not, the difference in marginal effects between the two groups represents a constant average effect.

[13]We limit appropriation tools to the use of patents in our analysis, as patents are the most widely used formal intellectual property rights tool for technological innovation.

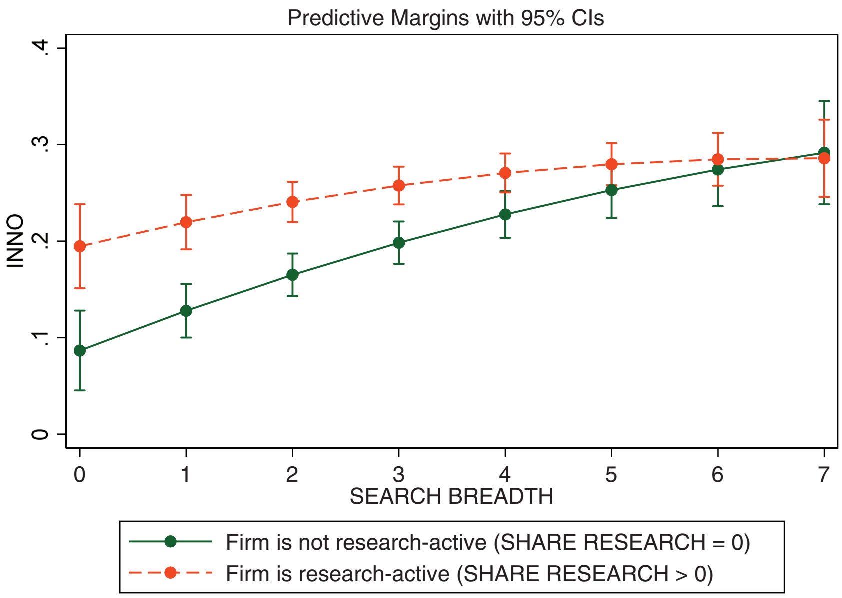


**FIGURE 4** Effect of *SEARCH BREADTH* on firm innovation depending on engagement in internal research (*SHARE RESEARCH*).

significant in the subsample of industries in which patenting is of little use in securing the returns from innovation (Column 2). Using seemingly unrelated regressions, we also explicitly test whether the interaction effect is statistically significant across Columns 1 and 2. The corresponding test statistic is 7.85, with a $p$-value of 0.0051, which shows that the differences are indeed statistically significant. This finding indicates that patents can mitigate spillover risks from the simultaneous engagement of firms in research and external search, thus supporting Hypothesis 3.

We further provide a complementary analysis of firm-level patent use (Columns 3 and 4). We find a highly significant negative interaction term for firms that do not consider patents an effective protection mechanisms, and a 10% significant interaction term for firms that do consider patents effective tools. However, when the equality of the coefficients of the interaction term across Columns 3 and 4 is tested, the null hypothesis of the coefficient equality is not rejected, meaning that there is no significant difference between the coefficients across regressions. This finding points out that sector-level appropriability plays a more important role than firm-level appropriability instruments.

## 4.3 | Sector-level heterogeneity

In this final extension, we perform a sector-level analysis. As Figures 1 and 2 show, industries vary in their average engagement in research and external search. We consider two key differentiations: (1) discrete versus complex sectors and (2) high-technology (HT) versus low-technology (LT) sectors. The first distinction is meaningful as it captures heterogeneity in appropriability and knowledge production, with complex sectors having a more strategic approach to the use of patenting and a higher level of cumulativeness of technological knowledge (Von Graevenitz et al., 2011). The distinction between high technology and low technology refers to the relative importance of R&D and innovation.[14] In high-technology contexts, the rate of innovation is much higher than that in low-technology contexts, which reduces the likelihood of knowledge crowding-out effects, while absorptive capacity gains in importance. Based on these distinctions, in Table 5, we show subsample regressions in Columns 1 and 2 for the discrete versus complex sectors and in Columns 3 and 4 for the high-technology versus low-technology sectors.

For all the subsamples, we observe significant positive effects of internal research and the breadth of search individually. The interaction effects of these two variables are consistently negative, with minor differences in terms of statistical significance and effect magnitude. In particular, the substitution effect appears slightly stronger for discrete sectors and low-technology sectors. This result is plausible from the point of view that complex sectors are more challenging to navigate,

[14]We follow the definition of high-technology versus low-technology sectors provided by the OECD. We group together the high-technology and medium high-technology sectors, and the medium low-technology and low-technology sectors (http://www.oecd.org/sti/industryandglobalisation/48350231.pdf).

**TABLE 4** Appropriability conditions.

| Variables | (1) INNO Sector-patent: High Coeff. (SE) | (2) INNO Sector-patent: Low Coeff. (SE) | (3) INNO Pat: Yes Coeff. (SE) | (4) INNO Pat: No Coeff. (SE) |
|---|---|---|---|---|
| SHARE RESEARCH | 0.029 (0.040) | 0.197*** (0.038) | 0.117* (0.066) | 0.135*** (0.031) |
| SEARCH BREADTH | 0.024 (0.016) | 0.064*** (0.015) | 0.042* (0.022) | 0.047*** (0.012) |
| SEARCH BREADTH sq. | −0.001 (0.002) | −0.003* (0.002) | −0.001 (0.003) | −0.002 (0.002) |
| SHARE RESEARCH × SEARCH BREADTH | −0.005 (0.011) | −0.044*** (0.010) | −0.030* (0.016) | −0.025*** (0.009) |
| **Wald test for coeff. equality** | **$Chi^2 = 7.85$ ($p$-value: 0.005)** | | **$Chi^2 = 0.07$ ($p$-value: 0.788)** | |
| FIRM-CONTROLS | YES | YES | YES | YES |
| INDUSTRY FE | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES |
| Observations | 9203 | 9533 | 3295 | 15,441 |
| Firm-ID's | 2350 | 2554 | 1115 | 4166 |

*Note*: The table shows regression results for identifying the mechanisms underlying the main findings. Models (1) and (2) show results of Tobit regressions using subsamples based on the average sector-level use of patenting as appropriation strategy. Models (3) and (4) show the results of a subsample analysis based on the firm-level use of patents as an appropriation strategy. The coefficient of interest (*SHARE RESEARCH* × *SEARCH BREADTH*) is tested across equations using seemingly unrelated regressions: The $Chi^2$ test statistic for coefficient equality between Columns (1) and (2) is 7.85 with a $p$-value of 0.005, thus the null-hypothesis of equality of coefficients is rejected. For the Columns (3) and (4), the test-statistic is 0.07 ($p$-value: 0.788), which implies that coefficients are not significantly different. All regressions include the complete set of firm-level controls as reported in Table 3. Standard errors are clustered by firm (in parentheses).

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

likely increasing the importance of absorptive capacity in overseeing all relevant technological developments (Fleming & Sorenson, 2004). Similarly, in high-technology sectors with a fast rate of technology development, doing research and a simultaneous engagement in external search are less likely to lead to knowledge crowding-out effects. However, importantly, when we formally test whether the effects differ across equations, we do not obtain statistically significant findings.[15] We can therefore conclude that the differences across subsamples are, if anything, marginal, which suggests that our main result and the underlying mechanisms are broadly applicable.

## 4.4 | Technical robustness tests

We conduct additional robustness tests to ensure that the main results of this study are not driven by idiosyncratic choices of our dependent variable and the internal research and external search measures. We report the results of these tests in the Appendix. First, in Table A4, we test variations related to our dependent variable. In particular, we introduce a 1-year time lag between our dependent variable and the independent variables, and test alternative outcome measures, namely the number of new patents filed (*LOG PATENT*) and a dummy variable that captures whether the firm introduced any new product or service innovation (*PRODUCT*) in a given year. These tests are helpful to mitigate concerns of reverse causality, as better innovation performance could affect firms' search and internal R&D strategies.

Second, in Tables A5 and A6, we introduce level-based measures of R&D (instead of the share), and interactions thereof with *SEARCH BREADTH*. Across all columns, the results remain identical to those reported in the main analysis (Tables 4 and 5). In particular, the interaction of the level of internal research with external search is significantly negative, unlike the equivalent interaction between internal development and external search.

Third, we replicate our main regressions and alternate our measurement of external search. We show the results in Table A7. In our main regressions, we follow the measure used by Laursen and Salter (2014), which consists of counting all the external knowledge sources ranked to be at least of medium importance to the firm. In Column 1, we rerun these specifications using the

[15]The formal test between Equations (1) and (2) yields a $Chi^2$ test statistic of 1.47 with a $p$-value of 0.2255, and the test between Equations (3) and (4) reveals a test statistic of 1.01 with a $p$-value of 0.3139.

**TABLE 5** Heterogeneity by sector technology intensity.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | INNO | INNO | INNO | INNO |
| | Discrete | Complex | HT | LT |
| | TOBIT | TOBIT | TOBIT | TOBIT |
| **Variables** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** |
| SHARE RESEARCH | 0.157*** (0.037) | 0.099** (0.046) | 0.112*** (0.041) | 0.141*** (0.039) |
| SEARCH BREADTH | 0.059*** (0.015) | 0.034** (0.017) | 0.040** (0.017) | 0.052*** (0.015) |
| SEARCH BREADTH sq. | −0.003 (0.002) | −0.002 (0.002) | −0.002 (0.002) | −0.002 (0.002) |
| SHARE RESEARCH ×SEARCH BREADTH | −0.036*** (0.010) | −0.017 (0.013) | −0.019* (0.011) | −0.034*** (0.010) |
| **Wald test for coeff. equality** | **Chi$^2$ = 1.47 (*p*-value: 0.2255)** | | **Chi$^2$ = 1.01 (*p*-value: 0.3139)** | |
| FIRM-CONTROLS | YES | YES | YES | YES |
| INDUSTRY FE | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES |
| Observations | 18,736 | 18,736 | 18,736 | 9423 |
| Firm-ID's | 4469 | 4469 | 4469 | 2190 |

*Note*: The table shows the results of subsample regressions based on sector-level technology characteristics. Column (1) shows the results for "discrete" sectors, whereas Column (2) shows the results for "complex" sectors. Columns (3) shows the results for High Technology and Medium High Technology sectors according to the definition of the OECD, and Column (4) Medium Low Technology and Low Technology sectors. The coefficient of interest (*SHARE RESEARCH × SEARCH BREADTH*) is tested across equations using seemingly unrelated regressions (SUEST): The Chi$^2$ test statistic for the coefficient equality between Columns (1) and (2) is 1.47 (*p*-value: 0.2255), and for the Columns (3) and (4) 1.01 (*p*-value: 0.3139). All regressions include the complete set of firm-level controls as reported in Table 3. Standard errors are clustered by firm (in parentheses).
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

measure suggested by Laursen and Salter (2006) of counting all external sources for as long as they are at least of low importance (as opposed to being of no importance), ignoring the precise degree of relevance attached to them. We further test a more restrictive measure that counts the sources only when they are of high relevance to the firm (Column 2). Finally, we construct a measure that considers formal, contractual-based collaborations as a measure of (hard) openness (Column 3), and in Column (4) we simultaneously test for the effects of hard openness and soft openness. Our results are insensitive to these variations in the measurement.

## 5 | DISCUSSION AND CONCLUSION

This paper analyzes the interplay between the nature of a firm's internal R&D and the sourcing of external knowledge to enhance firm innovation. We specifically focus on understanding the relationship between internally conducted research, relative to development, and the sourcing of external knowledge. Our empirical analysis first demonstrates that both firm internal research and the search for external knowledge independently have a positive effect on innovation performance. However, we also find that research-active firms benefit less from the simultaneous use of external knowledge. This substitution effect is a surprising result, as conducting research is typically associated with an augmented absorptive capacity that should enhance a firm's ability to identify and internalize external knowledge. We also find that this result can plausibly be attributed to "crowding out" and "spillover" effects. Firms engaged in research are often situated closer to the knowledge frontier, requiring more extensive and costly search efforts to identify valuable external knowledge that complements the outcomes from their own internal research. Moreover, the appropriability problem linked with internal research can intensify when firms also engage in external search, leading to increased unintended knowledge outflows.

These results offer important insights into the scholarly debate on the linkage between internal and external knowledge, and particularly the factors that influence their complementarity. We emphasize the pivotal role of the composition and nature of firm-internal R&D in terms of the relative weights of the R and D dimensions in achieving gains from external knowledge search. While a traditional view suggests that the search for external knowledge benefits from internal research based on an improved understanding of the technological landscape (Cockburn & Henderson, 1998; Escribano et al., 2009; Fleming & Sorenson, 2004), our findings suggest that the marginal improvements in absorptive capacity from research might be limited, conditional on constant R&D levels. Simultaneously, mechanisms leading to reduced external search effectiveness, such as greater difficulties to identify external knowledge that complements internal research findings, and increases in outgoing knowledge spillovers, gain in relevance when firms perform internal research. Therefore, our results complement related studies that suggest diminishing benefits of formal R&D collaborations when firms are close to the knowledge frontier (Grimpe & Sofka, 2016) and studies that highlight spillover concerns in the context of informal knowledge sourcing (Laursen & Salter, 2014).

Moreover, our study contributes to the discourse on the private returns to corporate science. Theoretically, research is linked to generating breakthrough technologies, but it also entails higher failure risks and knowledge spillovers compared with development (Arrow, 1962; Rosenberg, 1990). Empirically, most studies indicate a positive relationship with firm performance indicators, though sector and time heterogeneity exist (Arora et al., 2018, 2021; Czarnitzki & Thorwarth, 2012; Hsu et al., 2021; Simeth & Cincera, 2016). Our finding that greater shares of internal research improve innovation performance, while the value of external search diminishes, highlights both the advantages and challenges of performing research in the corporate domain. In other words, while research offers its merits, it simultaneously limits the benefits derived from external knowledge sourcing, contrary to the expectation that internal research would enhance external knowledge utilization unambiguously.

Our study also has important implications for firm managers. As internal research and external search each independently enhance innovation performance, but their complementarities are limited when performed simultaneously, managers can strategically allocate resources between them. In competitive environments with high spillover risks, firms may optimize innovation by leveraging external search and shifting internal R&D resources away from research toward development. Similarly, difficulties in the availability of scientifically trained personnel may promote external search and open innovation. Conversely, strong internal research capabilities and proximity to the technological frontier may justify reduced external search but higher relative resource allocations to internal research, especially when external technological opportunities are limited.

While our study provides valuable new insights, it contains some limitations that offer opportunities for future research. First, while our empirical approach leverages a representative firm-level dataset that includes a wide range of industrial sectors, it does not allow for causal inferences in the absence of exogenous variation in firms' external search activities and resource commitments to internal research. More detailed external information could corroborate our findings and allow for causal inference. Second, even though Spain is a major European economy, idiosyncrasies in its business environment may affect some of the outcomes of our study. Future research could analyze similar questions using other country contexts, thereby enhancing the generalizability of our findings. We also acknowledge the limitations of using survey data. Although the thorough documentation and the standardized nature of the Spanish PITEC survey should enable managers to understand the definitions of the various components of the R & D process and to report accurate values, one cannot exclude that the related questions may lead to measurement error. Finally, future studies could analyze additional moderating factors and contextual variables that are likely to influence the relationship between R&D and open innovation strategies.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## ETHICS STATEMENT

The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

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## APPENDIX A

**TABLE A1** Pairwise correlations (main variables).

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | INNO | 1.00 | | | | | | | | | | | | | |
| (2) | SHARE RESEARCH | 0.01 | 1.00 | | | | | | | | | | | | |
| (3) | SEARCH BREADTH | 0.07 | 0.08 | 1.00 | | | | | | | | | | | |
| (4) | R&D INTENSITY | 0.07 | 0.07 | 0.14 | 1.00 | | | | | | | | | | |
| (5) | FIRM SIZE | 0.04 | −0.05 | 0.08 | −0.04 | 1.00 | | | | | | | | | |
| (6) | PUBLIC FUNDING | 0.02 | 0.01 | 0.23 | 0.12 | 0.06 | 1.00 | | | | | | | | |
| (7) | COLLABORATION | 0.05 | 0.05 | 0.37 | 0.12 | 0.11 | 0.28 | 1.00 | | | | | | | |
| (8) | EXPORT | 0.04 | 0.01 | 0.04 | −0.04 | −0.03 | 0.06 | 0.03 | 1.00 | | | | | | |
| (9) | START-UP | 0.00 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | 0.02 | 0.00 | 1.00 | | | | | |
| (10) | SCIENCE PARK | 0.04 | 0.03 | 0.12 | 0.27 | −0.02 | 0.11 | 0.12 | −0.02 | −0.01 | 1.00 | | | | |
| (11) | BUSINESS GROUP | −0.02 | −0.03 | 0.07 | −0.09 | 0.23 | 0.05 | 0.10 | 0.02 | 0.04 | −0.03 | 1.00 | | | |
| (12) | PATENT | 0.07 | 0.04 | 0.17 | 0.14 | 0.06 | 0.12 | 0.15 | 0.10 | 0.00 | 0.11 | 0.05 | 1.00 | | |
| (13) | TRADEMARK | 0.02 | 0.04 | 0.12 | 0.03 | 0.05 | 0.05 | 0.10 | 0.05 | 0.02 | 0.05 | 0.01 | 0.28 | 1.00 | |
| (14) | LABOR PRODUCTIVITY | −0.02 | 0.03 | 0.02 | −0.09 | 0.07 | 0.00 | 0.00 | 0.03 | 0.00 | −0.06 | 0.16 | −0.02 | 0.00 | 1.00 |

**TABLE A2** Predictive margins in the baseline model (Table 3, Column 1).

| SHARE RESEARCH | Margins | SD | SEARCH BREADTH | Margins | SD |
|---|---|---|---|---|---|
| 0.00 | 0.206 | 0.009 | 0 | 0.139 | 0.018 |
| 0.10 | 0.211 | 0.008 | 1 | 0.176 | 0.011 |
| 0.25 (median) | 0.218 | 0.007 | 2 | 0.207 | 0.008 |
| 0.40 | 0.226 | 0.007 | 3 | 0.232 | 0.008 |
| 0.50 | 0.231 | 0.007 | 4 | 0.253 | 0.009 |
| 0.60 | 0.236 | 0.007 | 5 | 0.268 | 0.009 |
| 0.80 | 0.245 | 0.009 | 6 | 0.278 | 0.012 |
| 0.90 | 0.250 | 0.011 | 7 | 0.282 | 0.019 |
| 1.00 | 0.255 | 0.012 | | | |

*Note*: The table shows predictive margins for the variables *SHARE RESEARCH* and *SEARCH BREADTH*, corresponding to the baseline model without interaction effects (Table 3, Column 1).

**TABLE A3** Marginal effects of *SEARCH BREADTH* depending on different levels of *SHARE RESEARCH* (Table 3, Column 2).

| Level of SHARE RESEARCH | = 0.00 (25%) | | = 0.25 (median) | | = 0.80 (75%) | |
|---|---|---|---|---|---|---|
| SEARCH BREADTH | Margins | SD | Margins | SD | Margins | SD |
| 0 | 0.092 | 0.021 | 0.125 | 0.018 | 0.197 | 0.022 |
| 1 | 0.137 | 0.013 | 0.163 | 0.011 | 0.220 | 0.015 |
| 2 | 0.177 | 0.010 | 0.197 | 0.008 | 0.239 | 0.011 |
| 3 | 0.213 | 0.010 | 0.226 | 0.009 | 0.253 | 0.011 |
| 4 | 0.244 | 0.011 | 0.250 | 0.009 | 0.263 | 0.011 |
| 5 | 0.271 | 0.013 | 0.270 | 0.010 | 0.268 | 0.013 |
| 6 | 0.293 | 0.016 | 0.285 | 0.013 | 0.269 | 0.016 |
| 7 | 0.310 | 0.023 | 0.296 | 0.020 | 0.265 | 0.023 |
| 8 | 0.323 | 0.034 | 0.302 | 0.030 | 0.256 | 0.033 |

*Note*: The table shows predictive margins for the variable *SEARCH BREADTH* depending on three different levels of *SHARE RESEARCH*, corresponding to the estimation reported in Table 3, Column 2.

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**TABLE A4** Alternative lag structure and dependent variables.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **Dependent variable** | **INNO** | **LOG PATENTS** | **LOG PATENTS** | **PRODUCT** | **PRODUCT** |
| **Estimator** | **TOBIT** | **OLS** | **OLS** | **PROBIT** | **PROBIT** |
| | **1 year** | **Contemporary** | **1 year** | **Contemporary** | **1 year** |
| **Lag structure** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** |
| SHARE RESEARCH | 0.063** (0.026) | 0.010 (0.013) | 0.027 (0.017) | 0.184*** (0.067) | 0.090 (0.080) |
| SEARCH BREADTH | 0.043*** (0.010) | −0.009 (0.006) | −0.008 (0.007) | 0.252*** (0.026) | 0.224*** (0.032) |
| SEARCH BREADTH sq. | −0.002* (0.001) | 0.002** (0.001) | 0.003** (0.001) | −0.023*** (0.004) | −0.019*** (0.004) |
| SHARE RESEARCH × SEARCH BREADTH | −0.017** (0.007) | −0.008* (0.005) | −0.012** (0.006) | −0.040** (0.019) | −0.047** (0.023) |
| FIRM CONTROLS | YES | YES | YES | YES | YES |
| INDUSTRY FE | YES | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES | YES |
| Observations | 13,818 | 18,736 | 13,818 | 18,736 | 13,818 |
| Firm-ID's | 3721 | 4469 | 3721 | 4469 | 3721 |

*Note*: The table shows the results of regressions that use lags between dependent and independent variables, and alternative outcome indicators for firm innovation. In Column (1), we estimate our standard Tobit model with a lag of 1 year between dependent and independent variables. In Columns (2) and (3), we estimate the alternative outcome measure of the (log of the) number of new patents filed. In Columns (4) and (5), we estimate the alternative outcome indicator whether the firm introduced a product or service innovation (dummy). All regressions include the complete set of firm-level controls as reported in Table 3. Standard errors are clustered by firm (in parentheses).
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

**TABLE A5** Replicating the main regression with level-based measures of research and development (R&D).

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **INNO** | **INNO** | **INNO** | **INNO** | **INNO** |
| | **TOBIT** | **TOBIT** | **OLS** | **OLS (FE)** | **RE-TOBIT** |
| **Variables** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** |
| LOG RESEARCH | 0.006*** (0.001) | 0.009*** (0.002) | 0.005*** (0.001) | 0.004*** (0.001) | 0.009*** (0.001) |
| LOG DEVELOPMENT | 0.006*** (0.001) | 0.006*** (0.002) | 0.002* (0.001) | −0.000 (0.001) | 0.003** (0.001) |
| SEARCH BREADTH | 0.034*** (0.011) | 0.038*** (0.011) | 0.006 (0.007) | −0.001 (0.007) | 0.023*** (0.008) |
| SEARCH BREADTH sq. | −0.002 (0.001) | −0.002 (0.002) | 0.001 (0.001) | 0.001 (0.001) | −0.001 (0.001) |
| LOG RESEARCH × SEARCH BREADTH | | −0.001** (0.001) | −0.001* (0.000) | −0.001* (0.000) | −0.001*** (0.000) |
| LOG DEVELOPMENT × SEARCH BREADTH | | 0.000 (0.001) | 0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) |
| FIRM CONTROLS | YES | YES | YES | YES | YES |
| FIRM FE | NO | NO | NO | YES | NO |
| INDUSTRY FE | YES | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES | YES |
| Observations | 18,736 | 18,736 | 18,736 | 18,736 | 18,736 |
| Firm-ID's | 4469 | 4469 | 4469 | 4469 | 4469 |

*Note*: Table replicates the main regression analysis when the research and development measures are introduced in levels, as opposed to the share of research in R&D. Model (1) represents a baseline Tobit model without interaction effects, Models (2)–(5) contain the interaction effect between the variables of interest *LOG RESEARCH* and *SEARCH BREADTH as well as LOG DEVELOPMENT* with *SEARCH BREADTH*. Model (2) is estimated using a Tobit estimator and represents our preferred specification. Models (3) and (4) are OLS regressions without and with firm fixed effects, and Model (5) is estimated using a Random-Effects Tobit estimator. All regressions include the complete set of firm-level controls as reported in Table 3. Standard errors are clustered by firm (in parentheses).
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

**TABLE A6** Replicating the regressions on the appropriability regime with R&D levels.

| Variables | (1) INNO Sector-patent: High Coeff. (SE) | (2) INNO Sector-patent: Low Coeff. (SE) | (3) INNO Pat: Yes Coeff. (SE) | (4) INNO Pat: No Coeff. (SE) |
|---|---|---|---|---|
| LOG RESEARCH | 0.014*** (0.002) | 0.004* (0.002) | 0.008** (0.003) | 0.010*** (0.002) |
| LOG DEVELOPMENT | 0.005*** (0.002) | 0.004* (0.002) | 0.004 (0.003) | 0.006*** (0.002) |
| SEARCH BREADTH | 0.052*** (0.011) | 0.021* (0.011) | 0.036** (0.017) | 0.036*** (0.009) |
| SEARCH BREADTH sq. | −0.003** (0.002) | −0.001 (0.001) | −0.001 (0.002) | −0.002 (0.001) |
| LOG RESEARCH × SEARCH BREADTH | −0.002*** (0.001) | −0.000 (0.001) | −0.001* (0.001) | −0.001** (0.000) |
| LOG DEVELOPMENT × SEARCH BREADTH | 0.000 (0.001) | 0.000 (0.001) | −0.000 (0.001) | 0.000 (0.000) |
| **Wald test for coeff. equality** | **$Chi^2 = 4.28$ ($p$-value: 0.0386)** | | **$Chi^2 = 0.15$ ($p$-value: 0.702)** | |
| FIRM-CONTROLS | YES | YES | YES | YES |
| INDUSTRY FE | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES |
| Observations | 9203 | 9533 | 3295 | 15,441 |
| Firm-ID's | 2350 | 2554 | 1115 | 4166 |

*Note*: The table shows regression results for identifying the mechanisms underlying the main findings. Columns (1) and (2) show results of Tobit regressions using subsamples based on the average sector-level use of patenting as appropriation strategy. Columns (3) and (4) show the results of subsample analysis based on the firm-level use of patents as an appropriation strategy. The coefficient of interest (*LOG RESEARCH × SEARCH BREADTH*) is tested across equations using seemingly unrelated regressions. All regressions contain the full set of firm-level controls as reported in Table 3. Standard errors are clustered by firm (in parentheses).

Abbreviation: R&D, research and development.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

**TABLE A7** Replicating the main regression using alternative measures of external search.

| Dependent variable | (1) INNO TOBIT | (2) INNO TOBIT | (3) INNO TOBIT | (4) INNO TOBIT |
|---|---|---|---|---|
| **Variables** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** | **Coeff. (SE)** |
| SHARE RESEARCH | 0.145*** (0.037) | 0.091*** (0.020) | 0.070*** (0.019) | 0.131*** (0.028) |
| SEARCH BREADTH LS2006 | 0.055*** (0.013) | | | |
| SEARCH BREADTH LS2006 squared | −0.004** (0.001) | | | |
| SHARE RESEARCH × SEARCH BREADTH LS 2006 | −0.020*** (0.007) | | | |
| SEARCH BREADTH HIGH | | 0.024* (0.012) | | |
| SEARCH BREADTH HIGH squared | | 0.001 (0.002) | | |
| SHARE RESEARCH × SEARCH BREADTH HIGH | | −0.034*** (0.011) | | |
| COLLABORATION BREADTH | | | −0.004 (0.020) | −0.019 (0.020) |
| COLLABORATION BREADTH squared | | | 0.004 (0.003) | 0.005* (0.003) |
| SHARE RESEARCH × COLLABORATION BREADTH | | | −0.018** (0.009) | −0.006 (0.010) |
| SEARCH BREADTH | | | | 0.048*** (0.011) |
| SEARCH BREADTH squared | | | | −0.003* (0.001) |
| SHARE RESEARCH × SEARCH BREADTH | | | | −0.025*** (0.008) |
| FIRM CONTROLS | YES | YES | YES | YES |
| INDUSTRY FE | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES |
| Observations | 18,736 | 18,736 | 18,736 | 18,736 |
| Firm-ID's | 4469 | 4469 | 4469 | 4469 |

*Note*: Table shows the results of regressions when using alternative independent variables. In Column (1), the specification of Laursen and Salter (2006) is used, in Column (2) Search Breadth is restricted to sources that are of high importance to the firm, and in Column (3) the measure is constructed by counting the number of distinct formal collaboration partners ("hard openness"). Column (4) considers an additional interaction between collaboration breadth and the share of research in order to control for a potential confounding effect of formal collaborations. Standard errors are clustered by firm (in parentheses).
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.