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Reaching beyond low-hanging fruit: Basic research and innovativeness

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ABSTRACT

In this paper we examine the relationship between basic research and the innovativeness of innovations and how this relationship varies between internally- and externally-sourced innovations. In addition, building on Nelson's argument on the economics of basic research, we examine how the relation between basic research and innovativeness is conditioned by whether or not the firm is diversified and whether arguments about basic research and diversification built from Nelson (1959) hold for differently-sourced innovations. Using data from a large-scale survey of U.S. manufacturing firms, we provide some empirical evidence showing that basic research is associated with more innovative innovations. Furthermore, we show that for internally-generated innovations, this relation is moderated by whether or not the firm is diversified, consistent with Nelson's argument. However, for externally-sourced innovations, basic research has a direct association with more innovative innovations, consistent with the absorptive capacity argument regarding superior technical evaluation, with the moderation of diversification not observed. The results contribute to a better understanding of the different mechanisms through which basic research is related to the type of innovations commercialized by for-profit firms.

1. Introduction

What is the relationship between a firm's performing basic research and the innovativeness of its commercialized innovations? And, does the answer vary by whether the innovation is externally- or internally-sourced? By innovativeness, we mean more than just novelty (i.e., new or significantly improved; see OECD's Oslo Manual). Innovativeness does not necessarily imply radical or breakthrough innovation (Abernathy and Clark, 1985; Anderson and Tushman, 1990; Christensen and Rosenbloom, 1995). Rather, the concept of innovativeness highlights the relative difference between existing offerings and the focal innovation on any of several dimensions, including the technological distance (absolute novelty plus non-obviousness) of the underlying invention or the implementation gap required to practice the innovation (Cohen et al., 2021). Basic research is expected to be associated with generating more innovative innovations, both directly and indirectly, by providing the technological seeds for more innovative innovations (Akcigit et al., 2021). Basic research is also thought to increase R&D productivity by enhancing a firm's ability to recognize the value of new external information, assimilate it, and apply it to commercial ends (Arora and Gambardella, 1994; Cohen and Levinthal, 1989, 1990; Rosenberg, 1990). At the same time, basic research produces knowledge that is hard to appropriate for for-profit firms and generates high knowledge spillovers (Arrow, 1962; Mowery and Rosenberg, 1989). However, a key argument emerging from the classic work on the economics of innovation is that diversified firms are thought to have an appropriability advantage in capturing the returns from basic research due to the higher probability that the outcome of basic research can be applied in unexpected directions and different industries (Nelson, 1959; Stephan, 2010). This prior work then suggests three answers to this question: that firms doing basic research are likely to internally generate more innovative innovations, that this relation should also be observable for externally-sourced innovations, and that for internally-sourced innovations, this relation may be moderated by whether the firm is diversified or not.

Recent evidence suggests that during the last few decades, large firms may be withdrawing from basic research and relying more on external research from universities and start-ups (Arora et al., 2019;

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Larivière et al., 2018).[1] To the extent that basic research is associated with more innovative innovations, then this question of the relations between basic research and innovativeness under various contexts (internally- versus externally generated, diversified or not) is both theoretically interesting and substantively important for innovation strategy and policy. Although more innovative innovation is not always more profitable innovation, considering a Schumpeterian process of creative destruction and long-run economic growth (Aghion et al., 2014; Schumpeter, 1942), more innovative innovations, as they are more distant from current practice, may increase the chance for creative destruction.[2] If companies devote fewer resources toward basic scientific research, the direction of technical change may be tilted toward more incremental innovation. In turn, sourcing technology from the external environment may be equally challenging due to diminished technical evaluation capabilities resting on a lack of basic research performance.

Prior research, reviewed in the next section, provides some indirect empirical support for our concerns but also presents essential gaps. Several studies have shown a relationship between basic research and the characteristics of technical change. However, the results to date are primarily based, with few exceptions, on patents and citations, and reflect internally-generated technologies, albeit often incorporating knowledge spillovers. The outcome variables examined do not capture critical dimensions of the arguments about basic research and innovativeness. Furthermore, there exists mixed empirical evidence about Nelson's arguments regarding basic research and diversification, i.e., basic research and in-house innovation have different relations for firms that are diversified compared to those that are not.

The recently conducted American Competitiveness Survey (Arora et al., 2016) provides unique information about the innovativeness of product innovations commercialized by a representative sample of U.S. manufacturing firms, subsequently matched to scientific publications of the firms commercializing the innovations. The dataset covers over 5100 manufacturing firms in the US, including over 2600 innovating firms and over 1100 firms with new to the industry innovations. Furthermore, unlike many prior studies, the firms include both large, listed firms as well as SMEs that are not public firms. The measures of innovation are not limited to innovative activity (such as R&D and patenting), but use the Oslo Manual definition of innovation as new or improved products (goods or services) introduced into the market (OECD/Eurostat, 2018). Furthermore, the data includes measures of several indicators of the innovativeness of these innovations (Cohen et al., 2021). Finally, for new to the industry innovations, the dataset allows us to distinguish between those that were generated internally and those that were sourced externally (Arora et al., 2016).

While the data do not allow us to directly examine the causal impact of basic research on the innovativeness of firm innovations, the combined dataset enables us to explore the relationship between a firm's performing basic research and the innovativeness of its innovations (measured in several ways) under various contexts. In particular, we focus on a key firm characteristic, firm industry diversification, that the earlier literature highlighted as critical in moderating this relationship. While this claim has received limited – and mixed - empirical support, we highlight the specific contexts where we would and would not expect to see this relationship, providing new empirical support for one of Nelson's key arguments affecting firms' incentives to invest in basic research.

Our results suggest that firms that conduct basic research are more likely to launch more innovative product innovations. The relationship becomes significant and more salient when using a measure of innovativeness that reflects technical novelty or distance from current practice. Moreover, the relationship critically depends on whether the inventions underlying the innovations are generated internally (internal innovations) vs. sourced externally (external innovations). For internal innovations, a firm conducting basic research performance is associated with more innovative innovations only when the firm is diversified, i.e., operates in multiple industries. For external innovations, basic research performance is directly associated with more innovative innovations, consistent with the absorptive capacity argument (Cohen and Levinthal, 1989).

The results point to different mechanisms through which basic research is related to the type of innovations commercialized by for-profit firms. The significant interaction term between basic research and being diversified when predicting innovativeness of internally-sourced innovations is consistent with an argument that a key mechanism is the superior complementary assets held by multi-industry firms, allowing them to commercialize the outcome of basic research efforts where they are more likely to apply. For externally-sourced innovations, the direct relation is consistent with a key mechanism being that the acquiring firm has an enhanced ability to evaluate and select more innovative external technology. Our results are consistent with a concern that companies shifting away from basic research, even if they take advantage of markets for technologies, will produce an incrementalization of innovation, producing innovations that are less novel, less distant from current practice and hence reducing the chance for creative destruction in the economy.

2. Related literature

The relationship between in-house basic research and innovative performance has been covered extensively in the literature. However, much of the related work has developed in separate streams: one focusing on internally-generated innovation (often using patent data) and one, much more limited, focusing on externally-sourced innovation. These streams are reviewed below.

2.1. Basic research, internally-generated innovations, and external information flows

The question of why firms invest in basic research and its impact on innovative performance has been a classic question in the economics and innovation literature. Well-known contributions are the works of Nelson (1959), Griliches (1986), and Rosenberg (1990). Parts of this literature are reviewed by Dasgupta and David (1994), Cohen (2010), and Stephan (2010), among others.

Basic research may affect the rate and direction of technical change and, hence, the type of innovations firms introduce through different mechanisms. Starting from the classic work of Nelson, Rosenberg, and Griliches, the earlier literature has primarily worked under the assumption of internally-generated or "closed" innovation, albeit with spillovers. Key findings suggest that basic research tends to improve the internal R&D productivity of firms and is a crucial complement to more applied research (Akcigit et al., 2021; Hsu et al., 2021; Pavitt, 1991; Rosenberg, 1990). Basic research output can be immediately embodied into new products or added to the stock of knowledge available for future innovators (Akcigit et al., 2021). However, this benefit may vary by how capable the firm is or how varied the firm's opportunities are for using the output of basic research. While still focusing on internal R&D,

[1] NSF aggregate data suggest that the percent of R&D devoted to basic research between 1970 and 2020 has been quite stable in the U.S. at around 15–17 %, applied R&D around 20 %, and experimental development around 63 % (https://ncses.nsf.gov/pubs/nsb20225/data). These aggregate data, combined with evidence on a negative growth trend based on the scientific publication activity of large firms, documented by Arora et al. (2018, 2019), should then reflect an increased de-verticalization of the R&D process, whereby an increased fraction of basic R&D is conducted by universities and startups working within university ecosystems.

[2] For recent work incorporating the role of basic research as a key engine of economic growth using a Schumpeterian process of creative destruction, see Akcigit et al. (2021).

some pioneering contributions have highlighted the importance of internally-performed research as facilitating the absorption of *external* information, especially information originating from universities and government research labs, a key channel through which basic research is associated with greater *internal* R&D productivity (Cassiman and Veugelers, 2006; Cohen and Levinthal, 1989; Rosenberg, 1990). More recent work has shown that internally-performed basic research positively correlates with the innovativeness of internally-generated technologies using patent counts and patent forward citations (Cassiman et al., 2008). Internal basic research is also found to positively moderate the relation between internal R&D and patent counts weighted by citations, through better absorption of externally-conducted science (Leten et al., 2022).

In addition to the arguments about the association between basic research and the innovativeness of internally-generated innovations, diversified firms are thought to have an appropriability advantage in capturing the returns from basic research due to the higher probability that the outcome of basic research can be applied in unexpected directions and different industries in such firms (Nelson, 1959). When working on multiple independent projects simultaneously, scientists are more likely to see cross-fertilization and make a lateral connection among projects, which generates unexpected solutions (Simonton, 2003). In the same way, for firms conducting basic research, this cross-talk and recombination of ideas can occur and be further observed more often in multi-industry firms across different business units, resulting in more innovative innovations. Moreover, diversified firms have broader technological and downstream capabilities to successfully commercialize the uncertain outcome of basic research through vertical integration. While Nelson argues that diversified firms have a greater incentive to engage in basic research, this argument is based on the fact that basic research is more likely to generate internally usable innovations in diversified firms. While conducting basic research, diversified firms are more likely to generate more innovative solutions by operating in diverse product areas and building the capability of seeing unexpected solutions, and also more likely to be in a position to implement whichever innovative solutions are internally generated. Hence, the argument implies a positive interaction between conducting basic research and being diversified as predictors of more innovative innovations. The evidence on this effect, extensively reviewed by Cohen (2010), is mixed. Most work, however, has tested the hypothesis using measures of R&D or R&D intensity as the outcome variable, rather than innovation. Moreover, as Cohen clearly states, the Nelson hypothesis "implicitly assumes what Arrow (1962) expressed clearly: the market for information is imperfect and appropriability may be better achieved by the internal application of knowledge than by its sale." (Cohen, 2010:161). In other words, Nelson's hypothesis applies to a world of "closed innovation," leaving open the question of whether diversified firms have greater incentives to conduct basic research in-house in a world of more developed markets for technology.

Most prior work examining the impact of basic research on innovative performance has focused on its role in mediating or moderating external information flows, thus increasing internal R&D productivity. Empirically, studies of basic research have generally used outcomes such as number of patents (Gambardella, 1992) or patents weighted by forward citations (Cassiman et al., 2008; Fabrizio, 2009; Leten et al., 2022). Fabrizio (2009) shows firms conducting basic research benefit more from external university science, generating superior inventions. A few studies obtain similar results using innovations as the outcome. For example, Añón Higón (2016) finds a positive interaction between engaging in basic research and accessing external information from universities and research institutes as a predictor of pioneering innovations. Similarly, Martinez-Senra et al. (2015) find firms engaging in basic research generate superior product innovations through building high absorptive capacity.

2.2. Absorptive capacity, markets for technology, and the innovativeness of innovations

A second stream of research has focused on markets for technology (Arora et al., 2001; Arora and Gambardella, 1994). Such markets have grown significantly during the last few decades (Arora et al., 2001; Arora and Gambardella, 2010). Through licensing, acquisitions, or R&D alliances, markets for technology allow firms to source inventions from external markets. For example, about half of patents underlying new drugs commercialized by large pharmaceutical firms are generated externally (Ceccagnoli et al., 2010). Similarly, recent survey evidence suggests that, among US manufacturing firms' most important new-to-the-industry product innovations, almost half originated from an outside source (Arora et al., 2016).

Despite its importance, there is limited research examining the role of basic internal research on the type and features of innovations whose core underlying inventions have been generated externally (Arora and Gambardella, 2010). The most relevant work in this regard is the earlier study of Arora and Gambardella (1994), who apply Cohen and Levinthal's (1989) concept of absorptive capacity more explicitly to the world of markets for technology. Arora and Gambardella take a demand-side perspective and focus on the biopharmaceutical industry, a setting with relatively well-developed technology markets. They argue that scientific capabilities are critical for improving the technical evaluation of externally-generated technologies, leading large pharmaceutical companies to be more selective and to concentrate on fewer but more valuable external technologies. Arora and Gambardella (1994) provide evidence consistent with the theory, suggesting firms conducting relatively more basic research establish a lower number of alliances with external biotech firms. On the supply side of the market for technology, other research shows firms with a greater share of R&D devoted to basic research capture greater returns from licensing out technologies relative to internal commercialization and therefore have a greater willingness to license out their technologies (Arora and Ceccagnoli, 2006). Indeed, technology markets provide a way to capture returns from innovation for all firms, even those lacking diversified downstream capabilities, irrespective of where the in-house scientific research leads, again opening the question of whether Nelson's diversification hypothesis still holds in the context of more developed markets for technology.

2.3. The research gap

The previous literature leaves several open questions. First, there are arguments that there should be a positive relation between basic research and the innovativeness of internally-generated innovations, partly due to directly generating more innovative innovations and partly by increasing the productivity of R&D through better absorption of external information flows. Here, because basic research is generative of new, more innovative ideas (compared to existing knowledge in the firm and in the industry) and also because the uncertainty of basic research is likely to produce ideas that are less tethered to the existing practices of the firm, basic research is likely to be more innovative both in the technological sense and with reference to existing capabilities. Some prior studies examine an intermediate input to innovation by observing patents and patent citations (Cassiman et al., 2008; Leten et al., 2022). However, patents and citations do not capture aspects associated with the economic impact of basic research, such as the introduction of novel products into the marketplace, which often requires broad radical change in processes or distribution channels, or induces the creation of new markets or exit of some incumbents.

Second, despite its significant role emphasized in Nelson's pioneering 1959 study, the role of a firm's diversification on the relationship between basic research and the innovativeness of its innovations has received mixed and limited empirical support. As mentioned, one possibility is that the lack of support in prior studies relates to the prevalence of firms innovating through the acquisition of external inventions, where the Nelson hypothesis may not hold. In other words, internal sourcing of innovation may be a scope condition for the Nelson hypothesis.

Third, despite the growing importance of markets for technologies, prior studies neglect, with few exceptions, the relationship between basic research performance and the characteristics of externally-sourced innovations and instead more commonly focus on the absorption of external information that may increase internal R&D productivity. More generally, the link between basic research performance and the innovativeness of externally-acquired technologies is often only conceptualized and not empirically analyzed.

We take the first step in filling these gaps by providing novel empirical evidence regarding the association between basic research and the innovativeness of innovations commercialized by a large sample of U.S. innovating firms whose commercialized innovations may have originated internally or externally. The virtue of our data is that it allows us to examine innovations rather than inventions, consistent with Schumpeter (1939, p. 80). Focusing on innovation as an outcome will, first and foremost, enable us to provide evidence on the correlation between privately-conducted basic research and the introduction of new products into the marketplace by the firm performing basic research. Such evidence contributes to the debate about why firms perform basic research in-house and the role of product diversification and external sourcing of technology in moderating such incentives. At the same time, the results will inform whether basic research has some observable correlation with outcomes the literature associates with the Schumpeterian process of creative destruction.

3. Data and measures

3.1. Data

We will use the American Competitiveness Survey (Arora et al., 2016), which collects detailed information on firm innovations of various degrees of innovativeness as well as the division of innovative labor associated with those innovations, for firms in manufacturing and selected business services (overall response rate, 30.3 %). For this study, we use responses from a stratified sample of 5157 manufacturing firms with a minimum of ten employees, including both publicly traded and non-publicly traded firms, with post-sampling weights matched to U.S. Census data to adjust for sampling error and non-response bias (see Arora et al., 2016, for details).[3] The analyses below consider the survey design when estimating standard errors (Lee et al., 1989). The data contain measures of whether firms innovate, the innovativeness of the innovation along several dimensions (Cohen et al., 2021), the sources of the innovation (for those who had a new-to-industry innovation), in particular, customers, suppliers, and technology specialists such as universities and engineering firms, as well as sourcing from inside the firm. We supplement these data with data from the Web of Science tracking publications by firms and data from Dun & Bradstreet (D&B) measuring product industry diversification. We will use these data to model the innovativeness of firm innovation (and for each of externally- and internally-sourced innovations) as a function of basic scientific research, product industry diversification, and other control variables.

3.2. Measures

A key feature of the American Competitiveness Survey is that it asks the respondents if they have introduced any new or significantly improved product innovation in the last three years (2007–2009). If respondents said yes, then the survey asks the respondent to focus on a specific innovation (their ‘most important’ innovation that accounts for the most revenue in the last three years) and provide information on whether it was new-to-industry, i.e., introduced “in this industry before any other company,” along with other information, as explained below. This format allows linking the inputs and outcomes through specific innovations rather than more general sources of information questions or questions on the existence of patents or innovation-based sales in general (OECD/Eurostat, 2018).

3.2.1. Innovativeness

Following Cohen et al. (2021), we define innovativeness as the distance of the innovation from existing practice (on one or more dimensions). We measure the innovativeness of a firm’s innovation using two different measures (labeled *Innovativeness I* and *Innovativeness II*) that apply to different samples based on survey construction. First, following prior research that distinguishes between new-to-firm and new-to-industry innovations to represent the different degrees of novelty (Mansury and Love, 2008; Rodriguez et al., 2017), if a firm introduces a new or significantly improved product innovation that is *not* new-to-industry, we define it as having introduced a new-to-firm innovation. Our first measure, *Innovativeness I*, then captures whether the focal firm, conditional on introducing a new-to-firm innovation, introduces a new-to-industry versus a new-to-firm innovation.[4] Indeed, if a new-to-firm innovation is also a new-to-industry innovation, the innovation is relatively more innovative (i.e. more novel or less incremental). The result is a binary variable, where 1 means new-to-industry (and therefore also new-to-firm) and 0 means only new-to-firm, but not new-to-industry. This measure is conditional on the sample of firms that have introduced new or significantly improved product innovations (i.e., those who have no innovation are coded as missing). We examine related sample selection issues in our additional robustness tests.

Innovation surveys following the Oslo manual (OECD and Eurostat, 2009; OECD/Eurostat, 2018) include a similar question, especially the Community Innovation Survey (CIS) questionnaire in Europe (Mairesse and Mohnen, 2010). In particular, Duguet (2006) used a similar question from the pioneering French CIS survey to distinguish between radical versus incremental innovations and found that only radical innovations significantly correlate with total factor productivity growth. More recently, Añón Higón (2016) has used and related the same question to basic research, as reviewed in Section 2.

Second, we create another measure of innovativeness, *Innovativeness II*, for new-to-industry innovations. In the American Competitiveness Survey, the component questions for *Innovativeness II* were only asked of respondents who reported new-to-industry innovations, and so we only have this measure for new-to-industry innovators. Put differently, *Innovativeness II* is asking, among those who are Yes on *Innovativeness I* (i.e., whose focal innovation is relatively higher on innovativeness—new-to-industry rather than just new-to-firm), which are the more or less innovative innovations? Related sample selection issues will be further addressed in our additional robustness tests. We compute *Innovativeness II* by combining two underlying indicators of the distance of the focal innovation from existing products. The first captures how far the focal

[3] Arora et al. (2016) report non-response bias tests comparing D&B data for respondents and non-respondents and find the sample representative of the population on firm age, being multi-industry, region, or likelihood to export. Business units attached to Fortune 500 firms, large firms, multi-unit firms, public firms and pharmaceuticals were somewhat less likely to respond. To correct for response bias, the data include post-sample weights to match the response distributions to US Census data on industry, firm size and startup status.

[4] The two items are:*New-to-firm*: "In 2009, have you earned revenue from any new or significantly improved goods or services in [INDUSTRY] introduced since 2007, where “New” means new to your firm. Also, please exclude simple resale of goods purchased from others or purely aesthetic changes." (Yes/No) *New-to-industry*: [If Yes to new-to-firm] "Did you introduce this innovation in your industry before any other company?" (Yes/No)

innovation is removed from existing technology; the second reflects how different the focal innovation is from what the innovating firm has previously commercialized (Cohen et al., 2021).

First, the technological advance over existing technologies is what a patent examiner is charged with assessing when asked to evaluate both an invention's absolute novelty against prior art (Section 102 in the US patent law) and whether an invention is non-obvious (Section 103 in the US patent law; 'inventive step' in the European system). Hence, a technology that is granted a patent has been officially declared sufficiently distinct from existing technologies to have passed both of these requirements. Therefore, using questions in the survey, we first measure whether the innovation has a patent associated with it (*patented*), reflecting technical innovativeness. Note that the survey includes two questions, one asking if the innovating firm (who implemented the innovation) has a patent associated with the product and a second asking (for externally-sourced technologies) whether the source organization had patented the technology.[5] If the innovator patented any part of its innovation or its externally-acquired invention is patented (by the source organization), *patented* is yes (=1) and otherwise no (=0). Hence, we can capture patents associated with the innovation even if the innovating firm did not itself patent. Here we are not arguing that all patented innovations are radical or high value. Rather we are arguing that patented innovations are higher on the dimension of technical innovativeness (distance from existing technologies) than unpatented innovations. Of course, there can be innovations with high technical innovativeness that are not patented for other reasons, perhaps a preference for secrecy (Arundel, 2001; Cohen et al., 2002). Also, some patents have this declaration of novelty and non-obviousness overturned in court or at the Patent Trials and Appeals Board. Hence, there will be some measurement error in this measure, increasing standard errors and leading to conservative tests of significance (greater risk of false negatives). It is possible this measurement error also varies by the relative importance of patents in a given industry (Cohen et al., 2000). We control for industry fixed effects and firm-level factors related to patent propensity (size, startup) to address this issue. In addition, in our robustness checks in Appendix A, we test whether the results are affected by additional controls for patent propensity.

In addition, the management literature highlights that the commercialization of inventions, i.e., innovation, may be affected by the firm's internal and external capabilities such as expertise, equipment, the way the firm is managed or organized, and complementary technologies (Adner, 2006; Teece, 1986). Therefore, using questions in the survey, we also compute a measure of the *implementation gap,* i.e., whether, to commercialize the innovation, the innovator both acquired new equipment and personnel with distinct skills (item 1), and developed new distribution channels (item 2) (Cohen et al., 2021).[6] "Yes" for both questions means the *implementation gap* is large (=1), i.e., the firm needs to build substantially different capabilities, and otherwise small (=0). For example, differences in commercialization between traditional vaccines and mRNA vaccines for COVID-19 can be used to explain the concept of the implementation gap. While traditional vaccines (e.g. the one by AstraZeneca) can exploit existing storage and distribution systems, mRNA vaccines (e.g., the one by BioNTech/Pfizer), a new type of vaccine that is faster and cheaper to develop but less familiar, require being kept frozen and depend on a stable distribution system to prevent the breakdown of the vaccine.[7] Therefore, based on our measure, mRNA vaccines are associated with a larger implementation gap. Our *implementation gap* variable, however, measures only internal distance from the innovator's existing capabilities, not the external implementation gap, such as the absence of complementary goods, services, and technologies that support the sale of the innovation at the industry-level or external to the firm (Cohen et al., 2021). Hence, we again have some measurement error due to cases where, although this innovation is new-to-industry and required the new-to-industry innovator to invest in new capabilities for implementation, it could be the case that other firms had such capabilities. In this case, the absolute implementation gap for the most capable firm would be smaller than indicated by our measure, increasing standard errors and leading to conservative tests of significance (greater risk of false negatives). To partially address this measurement error, we will control for both industry-level and firm-level drivers of the implementation gap (such as firm size or age and other unobserved industry fixed effects) to better reflect the underlying innovativeness of the innovation.

We combine *patented* and *implementation gap* to create *Innovativeness II*. If *patented* is yes (=1) or *implementation gap* is large (=1), *Innovativeness II* is 1, otherwise 0. This measure indicates that the given innovation is substantially distinct from existing offerings based on technical novelty or the (firm-level) novelty of required complementary assets: i.e., it is patented or the given innovation has a large implementation gap. In other words, it is relatively more innovative than other innovations lacking these features. The result is an innovativeness index that is a multi-dimensional formative measure of the construct of innovativeness, where the defining characteristic of the construct is the innovation's distance from existing practices (at either the firm or industry level depending on the item) and where the construct is an additive function of its sub-dimensions, rather than the measures being a reflection of an underlying latent variable (MacKenzie et al., 2011). We code this as a binary variable, where being more innovative on either dimension is sufficient. Based on the arguments above, the greater innovativeness associated with basic research can express itself along either type (technological or implementation gap), and the uncertainty of basic research makes it likely that it is not predictable which of the two types will be expressed (and so modeling each sub-component separately would not properly capture the predicted relationship).

3.2.2. *Basic research*

We measure the basic research performance of the focal firm using the number of its basic science publications for the five-year period, from 2002 to 2006, i.e., a window before firms implement the focal innovations.[8] We conducted a thorough search of the firms in our sample, taking into consideration variations in their names, in order to identify all publications linked to these firms between 2002 and 2006. This search was performed using the "addresses" field within Web of Science. For this measure, we first used the Web of Science's "Research Area" fields assigned to every indexed journal. These subfields are classified into five larger fields: Arts & Humanities, Life Sciences & Biomedicine, Physical Sciences, Social Sciences, and Technology. We defined Physical Sciences as "basic" and Technology as "applied." We used NSFs classification for Life Science & Biomedicine to identify basic vs. applied disciplines.[9] We defined Arts & Humanities and Social Sciences as "non-STEM." Note that most publications are assigned to more

[5] The two items are:

1. Did your company patent any part of this innovation? (Yes/No)
2. [For externally-sourced new-to-industry innovations] Did this source have a patent on any part of this innovation? (Yes/No)

[6] The two items are:To commercialize this innovation, did you:1. "Develop new sales and distribution channels?" (Yes/No)2. "Buy new types of equipment, or hire employees with skills different from existing employees?" (Yes/No)

[7] https://www.phgfoundation.org/briefing/rna-vaccines (Accessed on Dec 21st, 2020)

[8] While the long-term stock of basic research findings might also contribute to innovativeness, if we assume a 16.67 % depreciation rate in this knowledge stock, any publications that are more than 5 years old would be fully depreciated.

[9] https://www.nsf.gov/statistics/nsf13327/content.cfm?pub_id=4266&id=4 (Accessed on Nov 23rd, 2020)

than one subfield. Using these classifications, we define a basic science publication as one with at least one basic science subfield assigned.

We then create the variable *Log basic pubs,* which is the log of one plus the number of basic science publications. This measure may underestimate the presence of basic research, given that some firms might do basic research but not publish. However, since scientists doing basic research have a strong interest in publishing (Stern, 2004), this bias may not be substantial. Similarly, publishing activity can also show that the firm is more serious about basic research or conducts formal basic research compared to those not publishing. Still, there may be measurement error in this indicator. Furthermore, for a robustness test, we also use a binary measure of basic science publication that has the value "1" if the firm has any basic science publication and otherwise "0", which may further mitigate the biases (since as long as the firm publishes some of its basic research, our measure would capture that).

3.2.3. Diversified

To measure if the firm is diversified, we use a simple measure from D&B, measuring whether or not the firm's product offerings span multiple industries (based on the D&B multiproduct indicator). As pointed out earlier, the literature suggests an advantage to spanning various industries (a binary distinction). Our approach is consistent with Mackey et al. (2017), who show that an indicator variable is more appropriate when the goal is comparing diversified vs. focused firms, not estimating the optimal degree of diversification, for firm value. However, since one might still prefer using some continuous measure, using a count of the number of 3-digit NAICS listed in D&B, we check our models with a continuous measure as a robustness check.

3.2.4. External vs. internal innovation (used for split sample analysis)

For *innovativeness II*, we further examine the impact of basic research and its interaction with diversification by splitting the sample based on externally- and internally-sourced innovation. For firms with a new-to-industry innovation, the survey asked who originated the innovation, that is, created the overall design, developed the prototype, or conceptualized the technology (for the most important innovation in the last 3 years).[10] Note that we are measuring whether the firm used external sources for its focal innovation, not simply whether the firm made use of outside *information* (cf. Laursen and Salter, 2006; Martinez-Senra et al., 2015). We define externally-sourced innovations as those innovations that are originated by a supplier, a customer, another firm in the same industry, a consultant, an independent inventor, or universities or government labs. Otherwise, this is an internally-sourced innovation. For example, the Pfizer COVID vaccine was externally sourced from BioNTech and hence would be coded as "1" on our measure. Half of the new-to-industry innovations in our sample were externally sourced (Arora et al., 2016).

3.2.5. Controls

We include a control for conducting R&D or not (from the survey, so this measure includes unlisted- as well as listed-firms), as this is likely to predict innovativeness, and we want to show the correlations associated with basic research net of doing research and development at all.[11] We also control for firm size (log of the number of employees); this variable may condition doing basic research and also innovativeness (especially *Innovativeness II*, as both patenting and firm capabilities may be related to size and age) (cf. Cohen, 2010). We also control for startups (defined as those that were established less than five years ago, using the survey data; the variable is also a control for firm age). Since the work of Schumpeter, startups are thought to be an important source of major product change (cf. Cohen, 2010). Young companies may have skilled human capital, often reflected by advanced degrees or unique skills of founders, that may favor the introduction of major product changes (Malerba and McKelvey, 2020). In addition, we control for being a subsidiary firm and being foreign-owned, as each of these might affect whether the responding firm conducts basic research, whether they are diversified, and perhaps also innovativeness. These variables may be associated with the organizational structure, managerial practices, and culture of the parent firm or within-firm knowledge flows that may be correlated with innovative search processes and outcomes (Argyres et al., 2020; Laursen, 2012). We also include whether a firm is public or private. Financial markets may exert pressure against long-term and risky investments or influence access to financing. The last five variables are all based on data from D&B. We also consider the fixed effects of 22 industries defined at the 3–4 digit NAICS, using data from D&B, which were confirmed by survey respondents (reducing measurement error in this variable), to control for underlying technological opportunities as well as other industry-specific characteristics. Because patent propensities vary by industry and firm size (Cohen et al., 2000), these variables will partially control for patent propensities. We also test our models by adding other patent propensity measures as well for a robustness check (described below).

4. Empirical specification

For each measure, *Innovativeness I* and *Innovativeness II*, we first estimate the following specification:

$$Innovativeness = \beta_1\ Basic + \beta_2\ Diversified + \boldsymbol{\gamma X} + e \tag{1}$$

Basic and *Diversified* represent our measures of basic research performance (in logs) and multi-industry (a dummy variable), and ***X*** represents a vector of control variables.

We then add the interaction between *Basic* and *Diversified*:

$$Innovativeness = \beta_1\ Basic + \beta_2\ Diversified + \beta_3 Basic \bullet Diversified + \boldsymbol{\gamma X} + e \tag{2}$$

When using *Innovativeness II*, we also split the sample based on whether the focal firm sourced the new-to-industry product innovation externally versus internally, estimating Eqs. (1) and (2) within the samples of externally- or internally-sourced innovations.

We estimate these equations using linear probability models (LPM). We also used logistic regression models as a robustness check. For most of the models presented estimated with the LPM, given the discrete measure of innovativeness and the fact that the main measure of basic research is logged, the estimated coefficient for *Basic* represents the percentage change in the probability of introducing a more innovative product innovation for a 1 % increase in the number of basic research publications.

5. Results

We begin by providing some basic correlations and descriptive statistics on basic research and R&D activity based on the full sample of firms in the survey, i.e., irrespective of whether the focal firm had introduced new-to-industry innovations or not. We provide estimates of population statistics, based on sampling weights (Kalton, 1983). In particular, Table 1 shows that firms in the U.S. manufacturing sector with an R&D unit (including innovators and non-innovators) conduct limited basic research activities, based on publications: on average, only 5 % of R&D performing firms have at least one basic science publication from 2002 to 2006 and those have, on average, only two basic science

[10] The question was: "Did any of the following originate this innovation, that is, create the overall design, develop the prototype or conceptualize the technology?". The answer choices included: "a supplier; a customer; another firm in your industry; consultant, commercial lab, or engineering service provider; an independent inventor; universities or government labs" [Check all that apply]. If the answer to any of these is yes, then the innovation is coded as externally sourced.

[11] The question was: "Does your company conduct R&D?" (Yes/No).

Table 1
Basic research performance between R&D performers and R&D non-performers.

	Conducting R&D	
	No	Yes
	($N = 2964$)	($N = 2070$)
% Basic	1.4 %	5.4 %
# Basic pubs	0.1	2.2

Notes:
% Basic indicates % of firms that have any basic science publication over the five year period 2002–2006.
# Basic pubs indicates the mean number of basic science publications over the five year period 2002–2006.

publications in the five year span. These values are comparable to what has been found in previous work (cf. Añón Higón, 2016). At the same time, basic research is more likely to be undertaken by firms with an R&D unit than those without an R&D unit (5 % vs. 1 % of firms).

Table 2 shows our study sample's descriptive statistics and correlation matrix, giving weighted means to account for the sample design and post-sample weighting to match Census data to reflect the underlying population. We use 5157 manufacturing firms (including innovating and non-innovating firms). However, due to the contingency questions in the survey, for some analyses, we use a limited sample of those firms. Therefore, Table 2 presents pairwise correlations. We discuss sample selection issues in the robustness tests section. Table 2 shows that 28 % of manufacturing firms conduct R&D. Overall, 36 % (including innovating and non-innovating firms) are diversified. When we limit the sample to new-to-firm innovators ($N = 2605$), 55 % conduct R&D, 3 % do basic research and 37 % are diversified. When we limit the sample to new-to-industry innovators ($N = 1150$), 94 % conduct R&D, 5 % conduct basic research, and 40 % are diversified. Among new-to-industry innovations, half of those are externally sourced. Innovations that are associated with any patent account for half of the new-to-industry innovations. About one-quarter of new-to-industry innovations involved investment in substantially different capabilities (i.e., are characterized by a large implementation gap). For the correlations between the variables in the limited sample for each regression model, see Appendix Tables A1A to A1D.

Appendix Table A2 breaks out several key variables by industry. The table shows that having at least one scientific publication is most common in drugs and semiconductors and least common in textile and wood (among all manufacturing firms and new-to-industry innovators). New-to-firm innovation is most common in computers, drugs, and semiconductors, with over 60 % of respondents reporting new-to-firm innovation, and least common in wood, petroleum, and non-metallic minerals (representing less than a third in each industry). For *Innovativeness I* (the share of new-to-industry, conditional on having new-to-firm), the highest share is found in petroleum, transportation, computers, and drugs. Note that petroleum has a low share of new-to-firm, but among new-to-firm, most are new-to-industry. For the others, the industries high on *Innovativeness I* are also high on new-to-firm. For *Innovativeness II*, beverage, apparel, semiconductors, and computers (as well as miscellaneous) are all high, with over 70 % yes (although the N for beverage is only 10). At the same time, primary metal, fabricated metal, and food are all low, with less than half yes. Within *Innovativeness II*, apparel, petroleum, drugs, and textiles all score high on having a patent associated with the innovation (either themselves or from the technology source), while wood, food, and primary metal all have low rates of having a patent associated with the invention. In contrast, beverage, wood, and printing all score high on the implementation gap, while drugs, furniture, and non-metallic minerals all score low. The two components of innovativeness have a low, negative correlation at the industry level ($r = -0.15$). Hence, *Innovativeness II* should be thought of as a formative indicator of innovativeness, meaning a change in any individual sub-component of the indicator is sufficient to produce a

Table 2
Descriptive statistics and pairwise correlations.

		N	Mean	STD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	New to Firm inno (NTF)	5157	0.42	0.49	0	1															
(2)	New to Industry inno (NTI)	4878	0.16	0.37	0	1	0.53														
(3)	Innovativeness I (among NTF)	2326	0.40	0.49	0	1															
(4)	Innovativeness II (among NTI)	1121	0.61	0.49	0	1															
(5)	Tech significance	1116	0.50	0.50	0	1				0.81											
(6)	Implementation gap	1136	0.24	0.43	0	1				0.46	0.07										
(7)	Ext (v. Int) innovation (among NTI)	1127	0.50	0.50	0	1		0.00	0.00	0.02	0.05	0.03									
(8)	Log Basic publications	5157	0.04	0.33	0	7.13	0.05	0.08	0.08	0.09	0.10	0.00	0.00								
(9)	Basic publications count	5157	0.65	19.20	0	1244	0.03	0.04	0.03	0.03	0.03	−0.01	0.00	0.56							
(10)	Diversified	5157	0.36	0.48	0	1	0.01	0.04	0.06	−0.08	−0.09	−0.03	−0.08	0.01	0.00						
(11)	R&D	5034	0.28	0.45	0	1	0.51	0.68	0.67	0.13	0.14	0.00	−0.07	0.12	0.05	0.04					
(12)	Public	5157	0.03	0.17	0	1	0.10	0.11	0.07	0.12	0.16	−0.05	0.00	0.20	0.08	0.02	0.17				
(13)	Subsidiary	5157	0.11	0.31	0	1	0.10	0.11	0.10	0.07	0.14	−0.08	0.03	0.21	0.07	−0.01	0.19	0.34			
(14)	Start up	5043	0.05	0.21	0	1	0.02	0.02	0.02	0.11	0.11	0.10	−0.01	−0.01	−0.01	−0.08	0.01	0.00	0.00		
(15)	Log employees	5136	3.33	0.94	0.69	8.99	0.14	0.15	0.12	0.08	0.14	−0.05	−0.02	0.08	0.03	0.09	0.19	0.17	0.17	−0.03	
(16)	Foreign	5157	0.04	0.19	0	1	0.07	0.07	0.06	0.07	0.09	−0.03	0.03	0.18	0.06	−0.01	0.15	0.00	0.41	−0.01	0.08

change in the value on the construct (MacKenzie et al., 2011). This is not surprising, as the point is that innovativeness can occur on any of several dimensions, which may be independent (Cohen et al., 2021), and we are trying to capture innovativeness along any of the dimensions.

Table 3 first examines the relationship between basic research and innovativeness for all innovations (both internally-generated and externally-sourced), showing a positive association for each of the measures, although the relation is not always statistically significant. For *Innovativeness I* measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations, Column 1 shows that basic research performance is associated with an increase in the innovativeness of innovation. A 1 % increase in the number of publications is associated with an increase in the probability of introducing a new-to-industry innovation relative to an new-to-firm innovation by 1.9 percentage points, although the relation is not statistically significant at conventional levels ($p =$ .23). For *Innovativeness II*, measured by substantial distinctiveness from existing offerings (i.e., it has been granted a patented or the given innovation had a large implementation gap), Column 3 shows that a 1 % increase in the number of publications is associated with a statistically significant increase in the probability of introducing a more innovative innovation, a change of 5.4 percentage points ($p <$ .001). The relationship between basic research and innovativeness becomes significantly larger (i.e., 0.019 vs. 0.054, $p <$ .10). Based on Column 3, when comparing having zero publication (log of 1) to having one publication (log of 2), for a single-product, non-R&D performing, private, non-subsidiary, non-startup, non-foreign-owned chemical firms with an average size of employees, having at least one publication increases the predicted probability of introducing a more innovative innovation by 4 percentage points (from 33 % to 37 %).

Being diversified across industries can help the firm apply the outcome of basic research in unexpected directions (Nelson, 1959), and hence, we also test if the basic to innovativeness relation is contingent on being diversified. Interestingly, when we examine across all innovations (combining internally- and externally-sourced), the results in Columns 2 and 4 show no contingency with being diversified. This is consistent with the mixed evidence on the relationship between basic research and diversification reviewed by Cohen (2010), who argues that Nelson's hypothesis implicitly assumes that "appropriability may be better achieved by the internal application of knowledge" (Cohen, 2010: p. 161). Indeed, this result motivates further analysis to underpin the mechanisms underlying the relations between basic research and innovativeness.

To examine this diversified contingency in more detail, we split the sample based on whether a product innovation was sourced internally versus externally. As discussed earlier, we would expect, per Nelson's hypothesis, the relationship between basic research and the innovativeness of the innovation to be critically conditioned by being diversified when the new-to-industry innovations are sourced (i.e., generated) internally. In turn, basic research is expected to be directly related to the innovativeness of externally-sourced innovations due to the "absorptive capacity" theory (Cohen and Levinthal, 1989). Note that, as previously mentioned, the sample can only be split when using the second measure of innovativeness, *Innovativeness II*, due to the construction of the survey questionnaire.

Columns 1 and 2 in Table 4 show that for externally-sourced innovations, innovations from firms conducting basic research are associated with higher innovativeness than those not conducting basic research. This association is somewhat larger compared to the coefficient estimated for the overall sample shown in Table 3, although the difference is not statistically significant (i.e., 0.067 vs. 0.054, $p =$ .40). Indeed, for externally-sourced innovations, Column 1 shows that a 1 % increase in the number of publications is associated with a 6.7 percentage point greater probability of introducing a more innovative innovation ($p <$ .001). When comparing having zero publications (log of 1) to having one publication (log of 2), for a single-product, non-R&D performing, private, non-subsidiary, non-startup, non-foreign-owned chemical firms with an average size of employees, having at least one publication increases the predicted probability of introducing a more innovative externally-sourced innovation by 5 percentage points (from 21 % to 26 %). This result is consistent with prior research suggesting that basic research performance is critical for identifying and selecting valuable external technologies. Moreover, the relation between basic research and innovativeness is not contingent on being diversified (Column 2), which shows the Nelson hypothesis does not hold for externally-sourced innovations. For internally-sourced innovations (cf. Column 3, Table 4), the relation between basic research and innovativeness is positive but not significant, although based on prior literature, this relation is expected to be positive and significant. However, the results in Column 4 show a positive and significant interaction coefficient for being both diversified and conducting basic research ($p <$ .05). In other words, these results are consistent with an interpretation that a key contingency underlying the relation between basic research and innovativeness of internally-sourced innovations is whether or not the firm is diversified, as argued by Nelson (1959). The positive relation between basic research and the innovativeness of internal innovation becomes more salient when the firm has more opportunities to implement new inventions and to recombine existing diverse internal sources of information (i.e., when it is diversified).

The results presented in Table 4 also provide a plausible explanation for the lack of significance at conventional levels between basic research and *Innovativeness I*. Such a relationship should be critically conditioned by the sourcing of innovation, as is the case of the *Innovativeness II* measure shown in Table 4. The coefficient for basic research reflects two different mechanisms affecting innovativeness. One relates to the relation between basic research and internally-generated innovations, another relates to the ability to select more valuable external inventions underlying the commercialized innovations. In other words, we conjecture that if we knew the sourcing of innovations for the full sample, including the observations with new-to-firm but not new-to-industry innovations, we would find a similar pattern as shown in Table 4, with basic research positively and significantly correlated with *Innovativeness I* only when the commercializing firm generates innovations internally and is multi-industry, while we would expect to see a significant and positive relation between basic research and innovativeness when sourcing innovations externally. Alternative explanations, such as the notion that a more precise estimation of the coefficient for basic research is attainable within the subset of industries that perform higher levels of basic research, receive limited support from the data and will be addressed in the upcoming robustness tests section.

6. Robustness tests

To check the robustness of our findings, we test our models with several different operationalizations. We report the results of our tests for selection effects in Tables 5-8. We then report the remaining robustness checks in the subsequent sections below, with tables available in Appendix A.

6.1. Selection models

First, our models are estimated for different subsets of the sample (those who innovate, those who have a new-to-industry innovation, those who source internally/externally), and, considering the structure of our data, one may wonder about the possibility and seriousness of a selection bias. To examine how serious the selection bias is, we apply a Heckman sample selection model. First, it may be hard to assume that the unobserved factors affecting new-to-industry innovation are not correlated with those affecting new-to-firm innovation. Therefore, we examine selection issues arising from using only firms that have a new-to-firm innovation to estimate the relation between basic research and new-to-industry innovation among this set of firms (i.e., *Innovativeness I*). To improve identification beyond functional form assumptions

Table 3
Basic research performance, diversification, and innovativeness.

	Innovativeness I				*Innovativeness II*			
	(1)		(2)		(3)		(4)	
	β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.019		0.021		0.054		0.047	
	(0.016)	0.230	(0.017)	0.218	(0.015)	0.000	(0.019)	0.014
Diversified	0.024		0.024		−0.072		−0.074	
	(0.023)	0.303	(0.023)	0.305	(0.043)	0.091	(0.044)	0.093
Log basic x Diversified			−0.004				0.016	
			(0.031)	0.889			(0.031)	0.597
R&D	0.652		0.652		0.171		0.171	
	(0.024)	0.000	(0.024)	0.000	(0.084)	0.042	(0.084)	0.042
Public	−0.020		−0.020		0.193		0.194	
	(0.041)	0.628	(0.041)	0.626	(0.049)	0.000	(0.049)	0.000
Subsidiary	−0.013		−0.013		−0.033		−0.033	
	(0.033)	0.687	(0.033)	0.687	(0.050)	0.511	(0.050)	0.513
Startup	0.069		0.069		0.280		0.280	
	(0.031)	0.025	(0.031)	0.025	(0.069)	0.000	(0.069)	0.000
Log employees	−0.005		−0.005		0.030		0.030	
	(0.010)	0.647	(0.010)	0.649	(0.016)	0.061	(0.016)	0.062
Foreign	−0.024		−0.024		0.128		0.127	
	(0.046)	0.601	(0.046)	0.600	(0.065)	0.048	(0.065)	0.049
Constant	0.066		0.065		0.468		0.469	
	(0.042)	0.121	(0.042)	0.122	(0.105)	0.000	(0.105)	0.000
Industry dummies	Yes		Yes		Yes		Yes	
N	2224		2224		1085		1085	
R2	0.454		0.454		0.119		0.119	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

associated with a Heckman selection model, we need an instrumental variable that affects the selection of firms into having a new-to-firm innovation but does not directly affect the outcome (new-to-industry v. new-to-firm) given new-to-firm innovations. For this sample selection, we use the firm's average sales (divided by 1 million to adjust the scale) from 2004 to 2006 (prior three years from our window 2007–2009) from D&B as an instrument. Prior literature has shown that performance above aspirations, net of other variables, depresses rates of innovation (Cyert and March, 1963; Greve, 2003). Based on this prior work, we can argue that those firms with higher sales may have a lower incentive to innovate immediately while performing at or above the satisficing level. Therefore, the firms with higher sales will be less likely to introduce new-to-firm innovations than those with lower sales (controlling for R&D). However, innovations being new-to-industry innovations, conditional on innovating, should be unrelated to the firm's recent sales (controlling for R&D) because new-to-industry innovation is often based on the firm's long-term plan for growth. Table 5 shows that in the first step (Column 1), the average sales of the three prior years are indeed negatively associated with having any new-to-firm product innovation ($p = .058$); however, the inverse Mills ratio in the second step is not significant (cf. Columns 2 and 3), suggesting the selection bias is not significant. In the corrected models, all results are consistent with the main results shown in Columns 1 and 2 of Table 3, where the coefficient for basic research predicting the probability of introducing a new-to-industry versus new-to-firm innovation is positive, although not statistically significant.

Second, we examine selection issues arising from using only firms that have a new-to-industry innovation to estimate the relation between basic research and *Innovativeness II* (Table 6) because it may be hard to simply assume that generating a new-to-industry innovation and generating an innovation that is technologically more advance or far removed from existing internal implementation capabilities are stochastically independent. We use capital intensity, i.e., real capital per employee, at the 6-digit NAICS from the NBER-CES data (Becker et al., 2021), as the instrumental variable predicting the probability of introducing a new-to-industry product innovation (vs. no new-to-industry product innovation, which includes firms that do not innovate and firms with only new-to-firm innovation). Previous endogenous growth models based on creative destruction have argued that capital accumulation and innovation are complementary processes (Aghion and Howitt, 1998). According to Aghion and Howitt (1998), higher capital stock will increase incentives to innovate by stimulating the demand for the products created by successful innovators and reducing the cost of capital in the long run, and thus it will reduce the capital component of the cost of R&D. Therefore, industry capital intensity may exogenously affect the probability that the focal firm introduces a new-to-industry innovation, but it is unlikely to affect technological novelty or distance from current practice, as is the case, empirically, in our sample. Column 1 in Table 6 shows that in the first step, capital intensity has a positive and significant relation to the probability of introducing a new-to-industry product innovation across the full sample of firms, including innovators and non-innovators. Columns 2 and 3, in turn, show that the inverse Mills ratio is not significant, suggesting no significant selection bias. The interaction term between basic research and diversification also remains positive and significant, consistent with results obtained without the selection correction. Our main results, therefore, continue to hold.

Third, generating more innovative innovations may not be independent of generating internally- vs externally-sourced innovations. For the selection of internally- vs externally-sourced innovations (or vice versa), we use the PayDex score from the D&B data as the instrumental

Table 4
Basic research performance, diversification, and innovativeness for external vs. internal innovations.

	Innovativeness II							
	External innovation				Internal innovation			
	(1)		(2)		(3)		(4)	
	β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.067		0.089		0.038		−0.018	
	(0.018)	0.000	(0.022)	0.000	(0.031)	0.225	(0.043)	0.675
Diversified	0.013		0.020		−0.142		−0.151	
	(0.060)	0.831	(0.062)	0.749	(0.060)	0.018	(0.061)	0.014
Log basic x Diversified			−0.058				0.110	
			(0.039)	0.140			(0.053)	0.040
R&D	0.219		0.219		0.166		0.168	
	(0.103)	0.035	(0.103)	0.035	(0.153)	0.277	(0.153)	0.271
Public	0.176		0.175		0.209		0.217	
	(0.071)	0.013	(0.070)	0.013	(0.075)	0.005	(0.075)	0.004
Subsidiary	−0.048		−0.049		−0.012		−0.011	
	(0.064)	0.448	(0.063)	0.440	(0.078)	0.882	(0.078)	0.891
Startup	0.259		0.260		0.217		0.216	
	(0.070)	0.000	(0.070)	0.000	(0.119)	0.069	(0.120)	0.071
Log employees	0.037		0.038		0.024		0.023	
	(0.021)	0.074	(0.021)	0.071	(0.023)	0.302	(0.023)	0.320
Foreign	0.145		0.147		0.080		0.083	
	(0.073)	0.048	(0.073)	0.044	(0.106)	0.450	(0.105)	0.432
Constant	0.360		0.358		0.519		0.523	
	(0.138)	0.009	(0.137)	0.009	(0.179)	0.004	(0.179)	0.004
Industry dummies	Yes		Yes		Yes		Yes	
N	539		539		534		534	
R2	0.194		0.195		0.139		0.141	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

variable. The PayDex score measures “a business's past payment performance” on a scale of 1 to 100.[12] A higher score indicates lower risk and a business's higher credibility to creditors. This score can capture liquidity constraints. Hall and Lerner (2010) suggest that liquidity constraints may affect the ability to finance internal investment in R&D, and hence, a higher score may induce a company to create technology internally, without necessarily affecting the innovativeness of an innovation.[13] D&B provides max and min scores each year for each business. We compute the average of max and min scores for each of the three relevant years (i.e., 2007 to 2009) and use the average of the three average scores. Results, shown in Tables 7 and 8 (Columns 1), show that the PayDexAvg is significantly associated with innovation being internally-sourced vs. externally-sourced (p = .021). Comparing the results with and without adjusting for selection for externally-sourced innovations first (i.e., Table 4 with Table 7), we find that, for externally-sourced innovations, the coefficient for the relation between increasing basic research publications by 1 % and introducing a more innovative innovation slightly declines from 0.067 ($p < .001$) (Column 1, Table 4) to 0.052 ($p < .05$) (Column 2, Table 7) due to adjusting for selection. Comparing the interaction term between basic research and diversification for results with and without selection correction results from Table 7 (Column 3) show that the Nelson hypothesis continues *not* to hold for externally-sourced innovation (coefficient is −0.074, p = .054, as opposed to an estimated coefficient of −0.058 with a p = .140 without selection, Table 4 Column 2). Columns 2 and 3 in Table 7 show that the selection effect (inverse Mills ratio) is significant ($p < .10$ in both cases) for the case of externally-sourced innovation. The results related to internally-sourced innovation show that the selection effects do not appear to be significant. Indeed, Columns 2 and 3 in Table 8 show that the inverse Mills ratio is not significant in both the models (i.e., with and without the interaction term). Our main results continue to hold. Basic research performance does not have a significant direct relation to the innovativeness of internally-sourced innovation, but it does have a positive and significant relation when interacted with the product diversification dummy. When controlling for selection, the coefficient is equal to 0.100, with p = .066, from Column 3, Table 8 versus a coefficient of 0.110 and p = .040 when not controlling for selection, as in Column 4 of Table 4.

What do we learn from estimating Heckman selection models? Although the limited availability of multiple instruments limits our ability to test instrument validity, and we cannot rule out other sources of bias, our results suggest that selection bias may only exist when estimating the model within the sample of external innovations. The significance of the estimated inverse Mills ratio suggests that unobserved factors from both the selection and main equations are significantly correlated, and it is plausible that some of these factors, such as unobserved firm capabilities or technological opportunities, are correlated with basic research performance. When controlling for selection bias, the estimated coefficient for the interaction between basic research and diversification decreases (i.e., becomes more negative), suggesting that making inferences on the relationship between basic research and innovativeness for the full sample of innovations using estimates from the subsample of external innovations would be misleading. Indeed, the coefficient is negative when estimating the model within the sample of

[12] https://www.dnb.com/resources/db-credit-scores-ratings.html (Accessed 12 Dec 2022)

[13] To the extent that internal R&D effort affects the propensity to patent an invention, our instrument would not be valid, because the PayDexAvg would indirectly affect one component of our innovativeness measure (i.e. whether the innovation is patented or not). Despite this possibility, a similar identification assumption is often used in the innovation literature, see for example Arora et al. (2008), where R&D effort is assumed not to affect the value of an innovation but only the number of innovations.

Table 5
Heckman selection model for new-to-firm (NTF) innovations.

	New to firm inno		New to industry inno		New to industry inno	
	First step		Second step		Second step	
	(1)		(2)		(3)	
	β		β		β	
	(SE)	p	(SE)	p	(SE)	p
Log basic pubs	−0.060		0.020		0.021	
	(0.047)	0.201	(0.019)	0.282	(0.020)	0.287
Diversified	−0.051		0.028		0.028	
	(0.059)	0.390	(0.025)	0.278	(0.026)	0.282
Log basic x Diversified					−0.003	
					(0.032)	0.923
R&D	1.564		0.653		0.653	
	(0.071)	0.000	(0.193)	0.001	(0.193)	0.001
Public	0.131		−0.024		−0.024	
	(0.141)	0.354	(0.044)	0.585	(0.044)	0.584
Subsidiary	−0.003		−0.017		−0.017	
	(0.094)	0.978	(0.034)	0.620	(0.034)	0.621
Startup	0.176		0.097		0.097	
	(0.251)	0.483	(0.052)	0.062	(0.052)	0.062
Log employees	0.127		−0.010		−0.010	
	(0.032)	0.000	(0.017)	0.550	(0.017)	0.551
Foreign	−0.155		−0.027		−0.027	
	(0.152)	0.307	(0.053)	0.609	(0.053)	0.608
Constant	−0.818		0.068		0.068	
	(0.130)	0.000	(0.278)	0.805	(0.278)	0.806
Avg sales04to06	−0.002					
	(0.001)	0.058				
IMR			0.017		0.018	
			(0.213)	0.935	(0.213)	0.934
Industry dummies	Yes		Yes		Yes	
N	4235		1925		1925	
F	23.88		44.35		43.05	
Prob > F	0.000		0.000		0.000	
R2			0.443		0.443	

Table 6
Heckman selection model for new-to-industry (NTI) innovations.

	New to Industry inno		*Innovativeness II*		*Innovativeness II*	
	First step		Second step		Second step	
	(1)		(2)		(3)	
	β		β		β	
	(SE)	p	(SE)	p	(SE)	p
Log basic pubs	0.052		0.068		0.062	
	(0.045)	0.248	(0.018)	0.000	(0.021)	0.004
Diversified	0.100		−0.042		−0.044	
	(0.081)	0.214	(0.049)	0.388	(0.050)	0.382
Log basic x Diversified					0.015	
					(0.030)	0.622
R&D	2.436		1.055		1.054	
	(0.098)	0.000	(0.706)	0.135	(0.706)	0.136
Public	−0.077		0.179		0.180	
	(0.119)	0.518	(0.050)	0.000	(0.050)	0.000
Subsidiary	−0.020		−0.047		−0.047	
	(0.102)	0.841	(0.052)	0.357	(0.052)	0.359
Startup	0.199		0.327		0.327	
	(0.127)	0.118	(0.080)	0.000	(0.080)	0.000
Log employees	0.030		0.036		0.036	
	(0.035)	0.386	(0.017)	0.036	(0.017)	0.037
Foreign	−0.252		0.067		0.067	
	(0.146)	0.084	(0.083)	0.416	(0.083)	0.417
Constant	−2.333		−0.718		−0.716	
	(0.173)	0.000	(0.954)	0.452	(0.954)	0.453
Capital intensity	2.200					
	(0.968)	0.023				
IMR			0.463		0.462	
			(0.371)	0.213	(0.371)	0.213
Industry dummies	Yes		Yes		Yes	
N	4681		1076		1076	
F	27.39		4.76		4.60	
Prob > F	0.000		0.000		0.000	
R2			0.122		0.122	

Notes: *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

external innovations, but it is positive when using the full sample of internal and external innovations. In other words, the existence of selection bias when splitting the sample into internal and external innovations is consistent with our key argument that the relationships among basic research, diversification, and innovativeness are different when considering internal and external innovations.

6.2. Unobserved heterogeneity

A variety of omitted variables may affect our results. We report several tests to see if our results are sensitive to alternative specifications designed to capture some forms of unobserved heterogeneity in the sample.

Applied research. First, the relation between basic research and innovativeness may depend on the amount of applied research conducted internally by the focal firm, which may be complementary to, and, therefore, positively correlated with, basic research activities (Hsu et al., 2021; Pavitt, 1991; Rosenberg, 1990). Using the same WoS fields-based method (described in Section 3.2), we define an applied research publication as a publication in a journal where the majority of field classifications are assigned to "applied" and then create the variable *Log applied pubs* which is the log of one plus the number of applied science publications. Results, presented in Table A3, are qualitatively consistent with our benchmark results. Interestingly, applied research performance tends to be uncorrelated with the various measures of innovativeness, as reflected by negative and insignificant estimates of its relation to innovativeness, except for the sample of internally-sourced innovations. Column 8 in Table A3 shows that a 1 % increase in applied research publications is associated with a 13 percentage points increase in the probability of introducing a more innovative innovation ($p = .039$). Our main results, however, are reinforced. When sourcing innovation internally, the relation between basic research and innovativeness is entirely conditioned by diversification.

Patent propensity. The unobserved patent propensity of the firm that generated the focal new-to-industry innovation may affect the rates of the new-to-industry innovation being patented (one component of our *Innovativeness II* measure). While we already control for industry fixed effects to capture this industry-level patent propensity (Arora et al., 2016; Cohen et al., 2000), we also test whether adding controls specifically for industry patent propensity changes our main results. We construct industry patent propensity measures in two different ways. First, if the industry of the focal firm heavily depends on startups as a source of innovation or if inventions are transferred through licenses as a major channel in the industry (de Rassenfosse et al., 2016; Gans et al., 2008), we can assume the industry is more likely to have a high patent propensity. Startups are more likely to patent any given invention to raise funding or enhance the reputation of the firm (Cohen et al., 2000; Haeussler et al., 2014). Patents, in turn, are a critical driver of technology licensing (Arora and Ceccagnoli, 2006; de Rassenfosse et al.,

Table 7
Heckman selection model for external innovations.

	External Innovation		*Innovativeness II*		*Innovativeness II*	
	First step		Second step		Second step	
	(1)		(2)		(3)	
	β		β		β	
	(SE)	p	(SE)	p	(SE)	p
Log basic pubs	0.048		0.052		0.081	
	(0.059)	0.414	(0.021)	0.012	(0.026)	0.002
Diversified	−0.173		0.104		0.115	
	(0.120)	0.149	(0.065)	0.112	(0.067)	0.087
Log basic x Diversified					−0.074	
					(0.038)	0.054
R&D	−0.400		0.315		0.317	
	(0.283)	0.158	(0.120)	0.009	(0.120)	0.009
Public	−0.069		0.218		0.217	
	(0.169)	0.683	(0.074)	0.003	(0.073)	0.003
Subsidiary	0.172		−0.115		−0.116	
	(0.151)	0.256	(0.071)	0.109	(0.071)	0.101
Startup	−0.198		0.385		0.388	
	(0.240)	0.410	(0.086)	0.000	(0.087)	0.000
Log employees	−0.006		0.031		0.032	
	(0.048)	0.906	(0.022)	0.159	(0.022)	0.151
Foreign	0.045		0.148		0.149	
	(0.200)	0.823	(0.075)	0.050	(0.075)	0.047
Constant	1.804		0.663		0.667	
	(0.715)	0.012	(0.236)	0.005	(0.236)	0.005
PayDexAvg	−0.020					
	(0.008)	0.021				
IMR			−0.510		−0.523	
			(0.306)	0.097	(0.306)	0.088
Industry dummies	Yes		Yes		Yes	
N	1030		514		514	
F	0.87		5.39		5.31	
Prob > F	0.676		0.000		0.000	
R2			0.195		0.197	

Notes: *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table 8
Heckman selection model for internal innovations.

	Internal Innovation		*Innovativeness II*		*Innovativeness II*	
	First step		Second step		Second step	
	(1)		(2)		(3)	
	β		β		β	
	(SE)	p	(SE)	p	(SE)	p
Log basic pubs	−0.048		0.042		−0.011	
	(0.059)	0.414	(0.034)	0.218	(0.046)	0.821
Diversified	0.173		−0.118		−0.126	
	(0.120)	0.149	(0.071)	0.097	(0.072)	0.080
Log basic x Diversified					0.100	
					(0.054)	0.066
R&D	0.400		0.184		0.184	
	(0.283)	0.158	(0.184)	0.319	(0.184)	0.316
Public	0.069		0.233		0.239	
	(0.169)	0.683	(0.076)	0.002	(0.077)	0.002
Subsidiary	−0.172		−0.047		−0.046	
	(0.151)	0.256	(0.085)	0.581	(0.085)	0.588
Startup	0.198		0.248		0.246	
	(0.240)	0.410	(0.130)	0.056	(0.130)	0.059
Log employees	0.006		0.015		0.014	
	(0.048)	0.906	(0.024)	0.520	(0.023)	0.541
Foreign	−0.045		0.028		0.030	
	(0.200)	0.823	(0.104)	0.784	(0.104)	0.769
Constant	−1.804		0.344		0.347	
	(0.715)	0.012	(0.423)	0.417	(0.423)	0.413
PayDexAvg	0.020					
	(0.008)	0.021				
IMR			0.302		0.303	
			(0.366)	0.410	(0.366)	0.409
Industry dummies	Yes		Yes		Yes	
N	1030		515		515	
F	0.87		3568.03		3944.87	
Prob > F	0.676		0.000		0.000	
R2			0.147		0.149	

Notes: *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

2016; Gans et al., 2008). Therefore, using our survey questionnaire, we compute the percentage of innovators in each industry that acquired inventions from startups[14] and also the percentage of innovators in each industry that acquired inventions through a license.[15] These measures are created at the disaggregate industry level (4-digit NAICS), and hence we can still control for the more aggregated industry dummies (3-digit NAICS). Controlling for these two measures jointly is presumed to capture exogenous drivers of industry patent propensity. This measure is more likely to be correlated with some of the explanatory variables when the focal innovation is internally generated, i.e. when the unobserved patent propensity relates to the focal firm. Even after controlling for these two measures, the results (shown in Table A4) are very similar to the main results. However, when innovation is externally sourced, the unobserved patent propensity that is correlated with innovativeness (in particular through its patenting component) relates to the input industry that generated the invention, reflecting firm patenting and licensing strategies in that industry (de Rassenfosse et al., 2016; Gambardella et al., 2007; Grimpe and Hussinger, 2014), in addition to the firm and industry characteristics captured by our size, startup, and industry fixed effects for the innovating firms. To capture this source of unobserved heterogeneity, we also construct an alternative measure of patent propensity, using the Bureau of Economic Analysis Input-Output tables to identify the major source industry for each respondent's industry, using the industry that accounts for the plurality of inputs. For each industry, we then use the survey questionnaire to compute the percentage of innovators in the input industry that patented any part of their innovations. When we use this measure as an additional control in our regressions, because of multicollinearity between 3-digit NAICS input industries and 3-digit NAICS output industries, we exclude industry dummies. All results (shown in Table A5) are again consistent with our benchmark results. The lack of any significant bias in estimating the relation between basic research and innovativeness when patent propensity is unobserved is not surprising in light of prior research suggesting that basic research is not correlated with patent propensity (Arora et al., 2008).

Type of externally-sourced innovations. Prior work has shown that firms conducting basic research benefit more from external university science than those not conducting basic research for generating superior inventions (Fabrizio, 2009). In turn, one could still argue the opposite, i.e. that firms conducting basic research may not be able to gain much from acquiring university-driven inventions (as opposed to accessing university science for internally-generated innovations) due to possible substitution effects. To test the possibility that the type of innovations

[14] The survey question is, for those who sourced the innovation externally, "Was this source a startup company, that is, a new, small company? Yes/No".

[15] The survey question is, for those who sourced the innovation externally, "How did you acquire this innovation? [Check all that apply]", with License as one of the choices.

sourced externally may condition the relation between basic research and innovativeness, we drop innovations sourced from universities or government labs from externally-sourced innovations and test our models. All results, shown in Table A6, are consistent.

Complementary capabilities. The ease of the implementation of a firm's innovation (one component of our combined innovativeness measure) can be dependent on firm size and age. The firm's experience in commercializing innovations determines complementary capabilities currently available in the firm. This unobserved experience is positively associated with the capabilities component of the innovativeness measure and may be correlated with basic research. Variables that are partly controlling for this potentially confounding relationship in our benchmark models are *startup* (based on age) and the focal firm's size (number of employees). To further probe the robustness of our results, we first test the models dropping *startups* from the sample (i.e., firms less than 5 years old) and find that all results are consistent (cf. Table A7). Second, we test the models excluding small firms from our sample, and similarly, find consistent results (cf. Table A8).

Technological opportunities. In our benchmark models, we control for industry-level technological opportunity using a full set of industry fixed effects. Yet, some drivers of technological opportunities may still be unobserved and could be correlated with both basic research and innovativeness, biasing our estimates. To further characterize industries as innovation intensive or not, a plausible indicator of technological opportunities, we compute the percentage of sales due to products that are new to the firm in each industry,[16] defined at a more detailed 4-digit NAICS classification level, and applying a cutoff of 10 observations of new-to-industry innovators per industry (Cohen et al., 2021). We then classify industries into high versus low innovation intensive industries based on whether the industry of the focal firm has a percentage of sales due to new-to-firm products above or below the median. Results adding the new dummy variable, *High inno intense*, are shown in Table A9. The new control for technological opportunities has a positive and significant coefficient ($p = .03$) when using *Innovativeness II* (Columns 3 and 4) for new-to-industry innovations and also for externally-sourced innovations. All conclusions for basic research and its interaction with diversified continue to be robust.

Demand shocks. Innovations in our sample have been introduced in the market during the 2007 to 2009 period, with respondents indicating the exact year of market introduction. Since this period includes the 2008 financial crisis, unobserved demand shocks may drive both innovativeness and investments in basic research. Table A10 shows results obtained by adding controls for year fixed-effects. Each of the year dummies (i.e., 2007, 2008) is not statistically significant individually or jointly, and including them does not affect our results.

Heterogeneity analysis. Perhaps basic research measured by publications may be more relevant in some industries than in others. For example, perhaps engaging in basic research matters most for industries that regularly engage in such activities, while for firms in less publication intensive industries, the relationship might not be observed. This cross-industry heterogeneity might be one explanation for the insignificant results found for the relation between basic research and *Innovativeness I*. While we control for industry fixed effects, this sort of industry-type heterogeneity in the relation of basic research to innovation is not controlled by the industry fixed effects. To explore this possibility, we also tested if our results hold across variation in industry publication activity. We split the sample into industries that are above and below the mean on publication activity (i.e. mean % basic research performers) among all manufacturing firms and then replicated our models across the two groups of industries. In Appendix Tables A11A and A11B we see the results. For the high publication industries, we see a positive relation between basic research and *Innovativeness I* ($p = .104$), while the relation is nearly zero for the low publication industries. For *Innovativeness II*, we see that for high publication industries, the relation is statistically significant ($p = .000$), while for low publication industries, the relation is not quite statistically significant ($p = .149$). However, the difference in the coefficients across the two models is not statistically significant (meaning we cannot reject the null that both coefficients are equal). When we examine external sourcing, we find that both coefficients (for high and low publication intensive) are positive and statistically significant ($p < .01$), and the coefficient for low publication intensive industries is larger (though the difference is not statistically significant). For internally-sourced innovation, for both groups of industries, the interaction term between basic research and diversified is positive ($p = .107$ for high publication industries and $p = .027$ for low publication industries), consistent with the Nelson hypothesis. Thus, overall, the results are consistent when we split the sample by high versus low publication intensivity, although there is some evidence that *Innovativeness I* is more strongly related to basic research for high publication intensive industries.

6.3. Alternative measures and functional forms

We also tested if our results were sensitive to alternative measures or to functional forms (additional results available from contact author). We find that the results are qualitatively robust to using either a binary coding for basic science publications, or a stricter coding that only counts a publication as basic research if the majority of field classifications for the journal are basic fields (Table A12). We also test our models measuring diversification using a continuous measure of the count of the number of different 3-digit NAICS assigned to the focal firm (D&B provides up to five NAICS), and all our conclusions remain robust. Finally, we also replicated our main results from Tables 3 and 4 using a logistic regression specification and the main results are all robust.

7. Conclusions

As many firms shift away from basic research, there is a concern that this might lead to the incrementalization of innovations introduced by the private sector. The economics of innovation literature suggests that internal basic research investments are critical drivers of the novelty of innovation introduced by firms, and also that this relation is critically conditioned by the extent to which they operate in a diversified set of industries (Nelson, 1959; Rosenberg, 1990). Most of the earlier literature focused on internally-generated innovations. In the last few decades, however, firms have shifted their focus to sourcing innovation externally (Arora et al., 2019; Chesbrough, 2003; Larivière et al., 2018), an activity that also benefits from strong basic research performance, albeit through a different mechanism. In particular, basic research performance has been shown to increase a firm's absorptive capacity (Arora and Gambardella, 1994; Cohen and Levinthal, 1989). Considering the relation between basic research and both internal and external innovation, a reduction of basic research, is therefore expected, all else equal, to be associated with lower innovativeness of firm innovation, with potentially negative relations with long-run firm performance and economic growth.

Our analysis, based on data available from the recent American Competitiveness Survey (Arora et al., 2016) provides a unique setting to examine the relationship between basic research and multiple indicators of the innovativeness of product innovations introduced by a representative sample of firms operating in a broad set of manufacturing industries, spanning both listed- and unlisted-firms, and including data on innovations (rather than proxying innovation through R&D or patenting). Moreover, because half of the new-to-industry innovations originated outside the firm, as opposed to internally, the data provide an opportunity to evaluate whether the direction and strength of the relationship between basic research and the innovativeness of innovation

[16] The survey question is, "In 2009, what percent of your revenues in [FOCAL INDUSTRY] is from new or significantly improved goods or services introduced since 2007?".

differs when the innovation originated in-house versus outside the focal firm.

Our findings suggest that basic research performance is positively associated with the innovativeness of product innovations commercialized by manufacturing firms, providing some initial support for the concerns raised above. The relationship is stronger and statistically more significant for new-to-industry innovations and when innovativeness is measured in terms of technological novelty or distance from the innovator's existing capabilities (*Innovativeness II*). This relation between basic research performance and the innovativeness of innovation appears through different mechanisms based on whether the innovation is sourced internally or externally. For internally-sourced innovations, this association is significantly moderated by whether a firm is diversified, as hypothesized by Nelson (1959). However, for externally-sourced innovation, stronger basic research performance is directly associated with more innovative innovations as argued by Arora and Gambardella (1994), who apply Cohen and Levinthal's (1989) concept of absorptive capacity for the superior technical evaluation of externally-generated technologies. These findings contribute to unpacking the different mechanisms of potentially benefiting from basic research performance for for-profit firms bridging the different streams of the existing literature on internally-generated vs. externally sourced innovations, often discussed separately.

7.1. Limitations

Our study has several limitations. First, one of our measures of the innovativeness of innovation is based on a combination of whether a new-to-industry innovation is *patented* or it created an *implementation gap* for the focal firm. We combined these measures because each captures different underlying features to create a formative indicator of the concept innovativeness (MacKenzie et al., 2011). However, future efforts leveraging different data can further develop different ways of measuring these concepts. For example, although information about patenting can be a measure of being more technologically novel, a large fraction of inventions are not patented. Considering this limitation, one can measure respondents' assessment of how novel the invention underlying the innovations is or whether the innovation reflects any technological advance at all, and to what extent (Cohen et al., 2021). Moreover, our current *implementation gap* measure captures only the internal distance from the innovator's existing capabilities, not the external implementation gap such as the absence of complementary products or services in the ecosystem. An alternative measure can include both internal and external implementation gaps. The implementation gap may also be measured by the extent to which the inventions underlying an innovation originate from other industries or reflect technologies that the firm does not typically employ (Cohen et al., 2021).

Second, there are several endogeneity concerns arising from selection and omitted variable biases. For example, there could be omitted variable bias resulting from the correlation of the returns to internal basic science with unobserved factors influencing innovativeness, such as technological opportunities unaccounted for by the industry fixed effects. Another possible omitted variable bias might be firm characteristics (resources, management) that would influence both the likelihood of engaging in basic research and the innovativeness of the firm's innovation. As we discussed in Section 3.2, our firm-level control variables (firm size, age, conducting R&D, being a subsidiary, being foreign-owned, public vs. private) may capture the effects of some omitted variables such as the organizational structure, resources, managerial practices, and culture of the firm (Argyres et al., 2020; Laursen, 2012). We also discuss several of these issues in the robustness section. Moreover, while such an omitted firm-level variable could potentially explain the correlation between basic research and innovativeness, it might be less likely that such a variable can simultaneously explain the distinct direct and interaction relations between innovativeness and basic research for internal and external innovations and in the presence and absence of diversification. Still, such an omitted variable cannot be ruled out given the cross-sectional observational data. One can also argue about reverse causality from using cross-sectional data, such that firms with more innovative innovations may become more diversified. Still, in this current case, it may be reasonable to assume that diversification is a fairly stable characteristic within a short time window. Moreover, the low correlations between diversification and the multiple measures of innovativeness in Table 2 indicate that this endogeneity is less likely in our case. While it is not clear how the multiple sources of endogeneity would affect the direction and magnitude of the estimated coefficients across samples, some additional instruments could improve our models. At this stage, the evidence presented should be interpreted as systematic and novel associations. We interpret the associations using some of the most established theories in the economics and management of innovation field.

7.2. Managerial and policy implications

Our results can be used to inform managers and policymakers to better understand the relationship between basic research and innovative performance. We recognize that more innovative innovations are not always better than incremental innovations, as the literature illustrates that substantial social (and private) welfare gains are often created from incremental innovations (Pisano, 2015; Rosenberg, 1982). However, considering a Schumpeterian process of creative destruction and long-run economic growth (Schumpeter, 1942), this study focuses on the role of basic research, a key driver of the innovativeness of innovations. For example, the literature suggests that more innovative innovations are more likely to lead to periodic shifts to entirely new technological paradigms by changing the foundations of scientific or technological knowledge underlying the products in an industry (Dosi, 1982). Some of the most recent work on economic growth seems to be aligned with this view (cf. Akcigit et al., 2021) and similarly emphasizes the key role of basic research in stimulating economic growth. We also note that there are concerns based on reports from prominent companies as well as overall trend data that show a de-emphasis on basic research during the last decades. Similarly, there has been a growing emphasis on sourcing innovations externally (as discussed by work on open innovation, markets for technology, and innovation ecosystems). While each of these strategies has much to recommend it, we examine the combination of external sourcing and basic research (as well as the alternative case of internal sourcing and basic research), with and without diversification. While the challenges of managing and financing basic research in for-profit firms remain daunting, a critical central question remains on how to increase the absorptive capacity of firms acquiring technology externally. Our results are consistent with the argument that basic research performance provides fundamental benefits for both internally-sourced as well as externally-sourced innovations, with the benefits coming from internal innovations accruing to the more diversified firms, and that may be why the most valuable technology companies today, such as Google, Microsoft, Apple, and Facebook, still produce a healthy rate of corporate publications in the most advanced field of technology (cf. Arora et al., 2020).

CRediT authorship contribution statement

Marco Ceccagnoli: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **You-Na Lee:** Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Data curation. **John P. Walsh:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix A

Table A1A
Descriptive statistics and correlations for observations in Table 3 columns (1–2).

		N	Mean	STD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Innovativeness I	2224	0.41	0.49	0	1								
(2)	Log basic pubs	2224	0.06	0.42	0	7.07	0.08							
(3)	Diversified	2224	0.37	0.48	0	1	0.06	0.01						
(4)	R&D	2224	0.54	0.50	0	1	0.66	0.10	0.06					
(5)	Public	2224	0.05	0.22	0	1	0.07	0.22	0.01	0.12				
(6)	Subsidiary	2224	0.14	0.35	0	1	0.10	0.21	−0.01	0.17	0.35			
(7)	Start up	2224	0.05	0.23	0	1	0.03	−0.02	−0.09	0.00	−0.02	−0.03		
(8)	Log employees	2224	3.50	1.04	0.69	8.52	0.12	0.09	0.08	0.19	0.17	0.17	−0.06	
(9)	Foreign	2224	0.05	0.22	0	1	0.06	0.17	0.00	0.10	−0.02	0.40	−0.01	0.09

Table A1B
Descriptive statistics and correlations for observations in Table 3 columns (3–4).

		N	Mean	STD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Innovativeness II	1085	0.60	0.49	0	1								
(2)	Log basic pubs	1085	0.10	0.52	0	7.07	0.09							
(3)	Diversified	1085	0.40	0.49	0	1	−0.08	0.01						
(4)	R&D	1085	0.94	0.24	0	1	0.12	0.03	−0.04					
(5)	Public	1085	0.07	0.25	0	1	0.12	0.26	−0.03	0.06				
(6)	Subsidiary	1085	0.18	0.38	0	1	0.06	0.22	−0.02	0.06	0.32			
(7)	Start up	1085	0.06	0.24	0	1	0.11	−0.03	−0.10	0.06	−0.03	−0.02		
(8)	Log employees	1085	3.64	1.14	0.69	8.52	0.08	0.09	0.04	0.13	0.19	0.22	−0.05	
(9)	Foreign	1085	0.06	0.24	0	1	0.07	0.16	0.01	0.04	−0.02	0.46	−0.02	0.11

Table A1C
Descriptive statistics and correlations for observations in Table 4 columns (1–2).

		N	Mean	STD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Innovativeness II	539	0.61	0.49	0	1								
(2)	Log basic pubs	539	0.12	0.59	0	7.07	0.11							
(3)	Diversified	539	0.37	0.48	0	1	−0.01	0.02						
(4)	R&D	539	0.93	0.25	0	1	0.16	0.03	−0.07					
(5)	Public	539	0.07	0.25	0	1	0.12	0.32	−0.02	0.07				
(6)	Subsidiary	539	0.20	0.40	0	1	0.07	0.20	−0.02	0.06	0.30			
(7)	Start up	539	0.05	0.23	0	1	0.14	−0.03	−0.15	0.05	0.01	0.07		
(8)	Log employees	539	3.64	1.13	0.69	8.52	0.12	0.12	0.04	0.07	0.17	0.25	0.02	
(9)	Foreign	539	0.07	0.25	0	1	0.10	0.12	0.05	0.05	−0.02	0.45	−0.01	0.10

Table A1D
Descriptive statistics and correlations for observations in Table 4 columns (3–4).

		N	Mean	STD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Innovativeness II	534	0.59	0.49	0	1								
(2)	Log basic pubs	534	0.08	0.45	0	6.02	0.07							
(3)	Diversified	534	0.43	0.50	0	1	−0.13	0.00						
(4)	R&D	534	0.95	0.22	0	1	0.10	0.04	0.00					
(5)	Public	534	0.07	0.25	0	1	0.12	0.19	−0.04	0.04				
(6)	Subsidiary	534	0.16	0.37	0	1	0.06	0.23	−0.01	0.06	0.34			
(7)	Start up	534	0.06	0.24	0	1	0.08	−0.03	−0.03	0.06	−0.05	−0.09		
(8)	Log employees	534	3.65	1.16	0.69	8.37	0.05	0.07	0.05	0.18	0.21	0.19	−0.11	
(9)	Foreign	534	0.06	0.23	0	1	0.04	0.22	−0.03	0.02	−0.03	0.46	−0.03	0.12

Table A2
Industry means of variables.

	All	% basic research	% multi	NTF inno	Inno I	NTI inno	% basic research	% multi	Inno II	Patented	Implement. gap	Externally-sourced
NAICS	N	% of all	% of all	% of all	% relative to NTF inno	N	% relative to NTI inno	% relative to NTI inno	% relative to NTI inno	% relative to NTI inno	% relative to NTI inno	% relative to NTI inno
311 Food Manufacturing	302	2.6	32	39	34	54	7.3	37	46	32	25	47
312 Beverage and Tobacco Product Manufacturing	60	2.1	46	43	44	10	2.3	67	93	59	70	41
313 Textile Mills	39	1.1	34	49	54	8	2.3	36	66	66	41	66
314 Textile Product Mills	76	0.0	37	36	51	12	0.0	40	60	40	28	60
315-6 Apparel, Leather and Allied Product Manufacturing	97	2.9	37	33	40	14	7.3	28	83	72	28	26
321 Wood Product Manufacturing	75	0.0	34	21	39	5	0.0	52	52	3	52	73
322 Paper Manufacturing	125	0.4	39	31	52	30	1.9	42	57	37	31	42
323 Printing and Related Support Activities	187	0.7	53	42	17	18	1.0	74	69	38	43	41
324 Petroleum and Coal Products Manufacturing	47	6.9	37	30	72	6	5.1	76	71	71	24	76
325 Chemical Manufacturing (except Pharmaceutical and Medicine)	318	5.3	39	52	50	97	9.8	37	54	46	16	49
3254 Pharmaceutical and Medicine Manufacturing	128	18.8	24	62	55	34	38.6	28	66	66	7	50
326 Plastics and Rubber Products Manufacturing	340	2.6	34	47	39	74	3.4	44	63	57	18	54
327 Nonmetallic Mineral Product Manufacturing	324	3.0	36	29	33	36	10.8	31	50	45	12	49
331 Primary Metal Manufacturing	325	2.2	35	38	26	44	3.7	31	40	36	20	49
332 Fabricated Metal Product Manufacturing	426	1.8	29	38	28	63	0.6	40	44	41	15	48
333 Machinery Manufacturing	389	2.5	40	45	49	103	1.5	37	68	58	19	49
334 Computer and Electronic Product Manufacturing (except Semiconductor)	287	7.3	37	67	56	108	11.4	41	72	62	27	46
3344 Semiconductor and Other Electronic Component Manufacturing	302	8.4	32	60	50	93	16.3	38	76	65	30	64
335 Electrical Equipment, Appliance, and Component Manufacturing	315	3.0	40	56	54	93	2.7	38	64	62	15	46
336 Transportation Equipment Manufacturing	344	2.4	37	50	57	102	2.9	41	55	46	23	53
337 Furniture and Related Product Manufacturing	263	1.1	39	41	37	41	0.4	33	51	44	10	50
339 Miscellaneous Manufacturing	388	2.1	32	55	46	105	6.1	37	75	59	37	48
All	5157	2.5	36	42	40	1150	4.9	40	61	50	24	50

Table A3
Robustness test: Controlling for applied research performance.

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.051		0.053		0.046		0.039		0.086		0.103		−0.041		−0.136	
	(0.030)	0.089	(0.029)	0.062	(0.034)	0.171	(0.035)	0.260	(0.045)	0.057	(0.045)	0.024	(0.074)	0.577	(0.077)	0.079
Diversified	0.024		0.024		−0.072		−0.074		0.014		0.020		−0.140		−0.152	
	(0.023)	0.302	(0.023)	0.303	(0.043)	0.090	(0.044)	0.093	(0.059)	0.819	(0.061)	0.744	(0.060)	0.019	(0.061)	0.013
Log basic x Diversified			−0.006				0.016				−0.055				0.139	
			(0.031)	0.858			(0.031)	0.600			(0.042)	0.187			(0.059)	0.020
R&D	0.652		0.652		0.171		0.171		0.220		0.219		0.167		0.170	
	(0.024)	0.000	(0.024)	0.000	(0.084)	0.042	(0.084)	0.042	(0.103)	0.034	(0.103)	0.034	(0.152)	0.274	(0.153)	0.266
Public	−0.014		−0.014		0.190		0.191		0.186		0.183		0.201		0.209	
	(0.041)	0.736	(0.041)	0.734	(0.050)	0.000	(0.050)	0.000	(0.075)	0.013	(0.074)	0.014	(0.074)	0.007	(0.074)	0.005
Subsidiary	−0.011		−0.011		−0.034		−0.034		−0.047		−0.048		−0.021		−0.023	
	(0.033)	0.728	(0.033)	0.728	(0.051)	0.505	(0.051)	0.506	(0.064)	0.466	(0.064)	0.456	(0.078)	0.783	(0.077)	0.765
Startup	0.069		0.069		0.280		0.280		0.259		0.260		0.217		0.216	
	(0.031)	0.026	(0.031)	0.026	(0.069)	0.000	(0.069)	0.000	(0.070)	0.000	(0.070)	0.000	(0.119)	0.070	(0.120)	0.072
Log employees	−0.004		−0.004		0.030		0.030		0.037		0.037		0.022		0.021	
	(0.010)	0.661	(0.010)	0.664	(0.016)	0.061	(0.016)	0.062	(0.021)	0.083	(0.021)	0.079	(0.023)	0.339	(0.023)	0.376
Foreign	−0.023		−0.023		0.127		0.127		0.145		0.146		0.073		0.075	
	(0.046)	0.621	(0.046)	0.620	(0.065)	0.049	(0.065)	0.049	(0.073)	0.049	(0.073)	0.045	(0.105)	0.486	(0.104)	0.474
Log applied pubs	−0.040		−0.041		0.010		0.010		−0.028		−0.022		0.100		0.130	
	(0.030)	0.180	(0.030)	0.176	(0.040)	0.793	(0.040)	0.793	(0.062)	0.652	(0.066)	0.743	(0.068)	0.141	(0.063)	0.039
Constant	0.064		0.064		0.469		0.469		0.361		0.358		0.527		0.534	
	(0.042)	0.128	(0.042)	0.130	(0.105)	0.000	(0.105)	0.000	(0.137)	0.009	(0.137)	0.009	(0.179)	0.003	(0.179)	0.003
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	2224		2224		1085		1085		539		539		534		534	
R2		0.454		0.454		0.119		0.119		0.194		0.195		0.141		0.145

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A4
Robustness test: Controlling for patent propensity (% inventions from start-ups, % inventions through license).

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.019		0.020		0.053		0.046		0.066		0.087		0.037		−0.018	
	(0.016)	0.242	(0.017)	0.226	(0.015)	0.001	(0.019)	0.017	(0.018)	0.000	(0.022)	0.000	(0.031)	0.237	(0.043)	0.673
Diversified	0.023		0.023		−0.075		−0.076		0.008		0.015		−0.144		−0.153	
	(0.023)	0.315	(0.023)	0.317	(0.042)	0.079	(0.044)	0.081	(0.059)	0.897	(0.061)	0.810	(0.059)	0.016	(0.061)	0.012
Log basic x Diversified			−0.004				0.017				−0.055				0.108	
			(0.031)	0.889			(0.031)	0.573			(0.039)	0.158			(0.053)	0.045
R&D	0.649		0.649		0.166		0.166		0.215		0.214		0.155		0.157	
	(0.024)	0.000	(0.024)	0.000	(0.084)	0.049	(0.084)	0.049	(0.105)	0.041	(0.105)	0.041	(0.151)	0.305	(0.151)	0.299
Public	−0.018		−0.018		0.196		0.197		0.184		0.182		0.210		0.217	
	(0.041)	0.667	(0.041)	0.665	(0.049)	0.000	(0.049)	0.000	(0.073)	0.012	(0.072)	0.011	(0.074)	0.005	(0.075)	0.004
Subsidiary	−0.012		−0.012		−0.035		−0.035		−0.052		−0.052		−0.014		−0.013	
	(0.033)	0.704	(0.033)	0.704	(0.050)	0.488	(0.050)	0.490	(0.064)	0.416	(0.064)	0.410	(0.077)	0.860	(0.077)	0.87
Startup	0.067		0.067		0.285		0.285		0.261		0.262		0.216		0.216	
	(0.031)	0.031	(0.031)	0.031	(0.070)	0.000	(0.070)	0.000	(0.070)	0.000	(0.070)	0.000	(0.120)	0.072	(0.120)	0.074
Log employees	−0.005		−0.005		0.032		0.032		0.039		0.039		0.024		0.023	
	(0.010)	0.630	(0.010)	0.631	(0.016)	0.054	(0.016)	0.055	(0.021)	0.070	(0.021)	0.067	(0.023)	0.303	(0.023)	0.321
Foreign	−0.024		−0.024		0.130		0.129		0.149		0.151		0.081		0.084	

(*continued on next page*)

Table A4 (*continued*)

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
	(0.046)	0.594	(0.046)	0.593	(0.064)	0.044	(0.064)	0.045	(0.074)	0.044	(0.073)	0.041	(0.105)	0.442	(0.105)	0.425
% Inv from SUs	−0.106		−0.106		−0.021		−0.021		−0.019		−0.013		−0.238		−0.230	
	(0.148)	0.472	(0.148)	0.472	(0.300)	0.945	(0.300)	0.944	(0.413)	0.963	(0.413)	0.975	(0.439)	0.588	(0.441)	0.603
% Inv through lic	0.222		0.222		0.250		0.251		0.254		0.244		0.216		0.211	
	(0.157)	0.158	(0.157)	0.158	(0.290)	0.389	(0.290)	0.388	(0.411)	0.536	(0.412)	0.554	(0.415)	0.602	(0.417)	0.613
Constant	0.054		0.054		0.436		0.437		0.328		0.326		0.538		0.541	
	(0.056)	0.333	(0.056)	0.335	(0.125)	0.000	(0.125)	0.000	(0.166)	0.048	(0.165)	0.049	(0.205)	0.009	(0.205)	0.008
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	2224		2224		1085		1085		539		539		534		534	
R2	0.455		0.455		0.120		0.120		0.195		0.196		0.140		0.143	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A5

Robustness test: Controlling for patent propensity (input industry % innovations patented).

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log Basic	0.016		0.010		0.042		0.025		0.041		0.045		0.043		−0.018	
	(0.016)	0.319	(0.017)	0.558	(0.016)	0.009	(0.018)	0.172	(0.018)	0.024	(0.016)	0.006	(0.033)	0.199	(0.042)	0.661
Diversified	0.018		0.017		−0.067		−0.071		0.014		0.015		−0.135		−0.145	
	(0.024)	0.463	(0.025)	0.494	(0.046)	0.143	(0.047)	0.133	(0.066)	0.836	(0.069)	0.828	(0.064)	0.036	(0.066)	0.029
Log Basic x Diversified			0.015				0.039				−0.010				0.119	
			(0.032)	0.636			(0.033)	0.239			(0.042)	0.812			(0.057)	0.038
R&D	0.649		0.649		0.204		0.204		0.310		0.310		0.149		0.151	
	(0.023)	0.000	(0.023)	0.000	(0.098)	0.038	(0.098)	0.038	(0.108)	0.004	(0.108)	0.004	(0.180)	0.408	(0.181)	0.404
Public	−0.042		−0.042		0.183		0.185		0.107		0.107		0.231		0.242	
	(0.044)	0.334	(0.044)	0.336	(0.050)	0.000	(0.050)	0.000	(0.067)	0.111	(0.067)	0.111	(0.075)	0.002	(0.076)	0.001
Subsidiary	−0.008		−0.008		−0.043		−0.044		−0.056		−0.056		−0.032		−0.031	
	(0.035)	0.823	(0.035)	0.822	(0.056)	0.435	(0.056)	0.431	(0.076)	0.458	(0.076)	0.460	(0.080)	0.689	(0.080)	0.696
Startup	0.059		0.059		0.225		0.225		0.256		0.256		0.178		0.176	
	(0.032)	0.068	(0.032)	0.070	(0.070)	0.001	(0.070)	0.001	(0.063)	0.000	(0.063)	0.000	(0.133)	0.181	(0.133)	0.187
Log employees	0.001		0.001		0.033		0.033		0.047		0.047		0.024		0.023	
	(0.011)	0.925	(0.011)	0.930	(0.017)	0.056	(0.017)	0.058	(0.025)	0.064	(0.025)	0.064	(0.024)	0.320	(0.024)	0.342
Foreign	−0.020		−0.020		0.133		0.133		0.174		0.174		0.075		0.076	
	(0.047)	0.671	(0.047)	0.673	(0.066)	0.045	(0.066)	0.046	(0.086)	0.044	(0.086)	0.044	(0.099)	0.448	(0.099)	0.443
Input Industry pat	0.045		0.045		0.192		0.191		0.309		0.309		0.088		0.084	
	(0.067)	0.506	(0.067)	0.507	(0.132)	0.145	(0.132)	0.146	(0.197)	0.117	(0.197)	0.118	(0.187)	0.640	(0.188)	0.654
Constant	0.032		0.033		0.232		0.234		0.036		0.035		0.356		0.363	
	(0.044)	0.470	(0.044)	0.464	(0.119)	0.051	(0.119)	0.049	(0.136)	0.793	(0.136)	0.795	(0.201)	0.077	(0.202)	0.073
N	2070		2070		1022		1022		508		508		502		502	
R2	0.433		0.433		0.061		0.062		0.092		0.092		0.056		0.059	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A6
Robustness test: Dropping innovations sourced from universities or government.

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.020		0.022		0.054		0.049		0.075		0.100		0.038		−0.018	
	(0.018)	0.264	(0.018)	0.203	(0.017)	0.002	(0.020)	0.016	(0.023)	0.001	(0.026)	0.000	(0.031)	0.225	(0.043)	0.68
Diversified	0.024		0.025		−0.096		−0.097		−0.034		−0.025		−0.142		−0.151	
	(0.024)	0.300	(0.024)	0.298	(0.044)	0.029	(0.045)	0.032	(0.064)	0.594	(0.066)	0.709	(0.060)	0.018	(0.061)	0.014
Log basic x Diversified			−0.008				0.013				−0.092				0.110	
			(0.038)	0.828			(0.037)	0.721			(0.054)	0.090			(0.053)	0.040
R&D	0.646		0.646		0.160		0.160		0.183		0.181		0.166		0.168	
	(0.024)	0.000	(0.024)	0.000	(0.084)	0.059	(0.084)	0.058	(0.104)	0.079	(0.104)	0.083	(0.153)	0.277	(0.153)	0.271
Public	−0.026		−0.027		0.196		0.197		0.178		0.174		0.209		0.217	
	(0.042)	0.536	(0.042)	0.531	(0.051)	0.000	(0.051)	0.000	(0.079)	0.025	(0.077)	0.025	(0.075)	0.005	(0.075)	0.004
Subsidiary	−0.016		−0.016		−0.016		−0.016		−0.011		−0.010		−0.012		−0.011	
	(0.034)	0.638	(0.034)	0.639	(0.053)	0.761	(0.053)	0.760	(0.071)	0.876	(0.071)	0.893	(0.078)	0.882	(0.078)	0.891
Startup	0.081		0.081		0.282		0.282		0.245		0.246		0.217		0.216	
	(0.030)	0.007	(0.030)	0.007	(0.072)	0.000	(0.073)	0.000	(0.080)	0.002	(0.081)	0.002	(0.119)	0.069	(0.120)	0.071
Log employees	−0.004		−0.004		0.026		0.026		0.028		0.028		0.024		0.023	
	(0.010)	0.683	(0.010)	0.685	(0.017)	0.124	(0.017)	0.125	(0.022)	0.207	(0.022)	0.203	(0.023)	0.302	(0.023)	0.320
Foreign	−0.027		−0.027		0.117		0.117		0.133		0.142		0.080		0.083	
	(0.047)	0.564	(0.047)	0.566	(0.070)	0.096	(0.071)	0.098	(0.087)	0.129	(0.087)	0.103	(0.106)	0.450	(0.105)	0.432
Constant	0.068		0.068		0.486		0.486		0.406		0.407		0.519		0.523	
	(0.043)	0.115	(0.043)	0.116	(0.107)	0.000	(0.107)	0.000	(0.143)	0.005	(0.143)	0.005	(0.179)	0.004	(0.179)	0.004
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	2148		2148		1015		1015		469		469		534		534	
R2	0.449		0.449		0.123		0.123		0.202		0.203		0.139		0.141	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A7
Robustness test: dropping start-ups.

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.021		0.022		0.055		0.048		0.065		0.091		0.037		−0.024	
	(0.016)	0.203	(0.017)	0.200	(0.015)	0.000	(0.019)	0.011	(0.018)	0.000	(0.022)	0.000	(0.032)	0.252	(0.044)	0.588
Diversified	0.026		0.026		−0.079		−0.081		0.017		0.026		−0.168		−0.179	
	(0.024)	0.283	(0.024)	0.287	(0.044)	0.074	(0.045)	0.077	(0.060)	0.773	(0.063)	0.681	(0.062)	0.007	(0.064)	0.005
Log basic x Diversified			−0.003				0.016				−0.068				0.118	
			(0.032)	0.919			(0.031)	0.613			(0.039)	0.083			(0.054)	0.031
R&D	0.640		0.640		0.173		0.173		0.215		0.214		0.166		0.168	
	(0.025)	0.000	(0.025)	0.000	(0.085)	0.042	(0.085)	0.042	(0.106)	0.043	(0.106)	0.044	(0.153)	0.277	(0.153)	0.271
Public	−0.012		−0.012		0.220		0.221		0.202		0.199		0.219		0.227	
	(0.042)	0.775	(0.042)	0.773	(0.050)	0.000	(0.050)	0.000	(0.074)	0.007	(0.073)	0.007	(0.076)	0.004	(0.077)	0.003
Subsidiary	−0.018		−0.018		−0.041		−0.041		−0.029		−0.029		−0.016		−0.015	
	(0.034)	0.590	(0.034)	0.590	(0.052)	0.428	(0.052)	0.43	(0.067)	0.669	(0.067)	0.666	(0.078)	0.843	(0.078)	0.853
Log employees	−0.006		−0.006		0.025		0.025		0.038		0.038		0.021		0.020	
	(0.011)	0.539	(0.011)	0.540	(0.017)	0.129	(0.017)	0.131	(0.022)	0.088	(0.022)	0.082	(0.024)	0.379	(0.024)	0.402
Foreign	−0.026		−0.026		0.150		0.150		0.143		0.145		0.101		0.104	
	(0.048)	0.581	(0.048)	0.580	(0.066)	0.024	(0.066)	0.024	(0.078)	0.069	(0.078)	0.064	(0.107)	0.348	(0.107)	0.328
Constant	0.074		0.074		0.484		0.484		0.356		0.353		0.536		0.541	
	(0.044)	0.090	(0.044)	0.091	(0.108)	0.000	(0.108)	0.000	(0.145)	0.015	(0.145)	0.015	(0.181)	0.003	(0.181)	0.003

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Table A7 (*continued*)

Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2086	2086	1015	1015	503	503	501	501
R2	0.441	0.441	0.113	0.113	0.186	0.187	0.143	0.146

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A8
Robustness test: Dropping small firms.

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.027		0.029		0.052		0.059		0.058		0.091		0.041		−0.007	
	(0.015)	0.068	(0.018)	0.108	(0.016)	0.002	(0.021)	0.01	(0.019)	0.002	(0.022)	0.000	(0.033)	0.215	(0.045)	0.872
Diversified	0.053		0.054		−0.090		−0.085		−0.005		0.023		−0.172		−0.194	
	(0.037)	0.151	(0.039)	0.164	(0.053)	0.091	(0.057)	0.14	(0.071)	0.946	(0.077)	0.762	(0.071)	0.016	(0.075)	0.010
Log basic x Diversified			−0.004				−0.017				−0.087				0.096	
			(0.028)	0.882			(0.033)	0.6			(0.038)	0.024			(0.056)	0.089
R&D	0.627		0.627		−0.213		−0.214		−0.152		−0.159		−0.467		−0.471	
	(0.033)	0.000	(0.033)	0.000	(0.095)	0.026	(0.095)	0.03	(0.122)	0.217	(0.126)	0.208	(0.105)	0.000	(0.106)	0.000
Public	0.008		0.008		0.217		0.217		0.285		0.288		0.123		0.130	
	(0.045)	0.864	(0.045)	0.866	(0.057)	0.000	(0.057)	0.000	(0.073)	0.000	(0.072)	0.000	(0.089)	0.169	(0.091)	0.153
Subsidiary	−0.008		−0.008		0.024		0.024		0.008		0.008		0.074		0.072	
	(0.040)	0.834	(0.040)	0.836	(0.058)	0.676	(0.058)	0.67	(0.071)	0.913	(0.071)	0.915	(0.078)	0.343	(0.078)	0.354
Startup	0.168		0.168		0.309		0.310		0.255		0.249		0.205		0.199	
	(0.085)	0.048	(0.085)	0.048	(0.110)	0.005	(0.111)	0.005	(0.177)	0.150	(0.180)	0.167	(0.180)	0.256	(0.178)	0.266
Log employees	0.018		0.018		0.053		0.053		0.037		0.039		0.057		0.055	
	(0.013)	0.156	(0.013)	0.155	(0.018)	0.003	(0.018)	0	(0.022)	0.097	(0.022)	0.075	(0.026)	0.027	(0.026)	0.031
Foreign	0.029		0.029		0.118		0.119		0.209		0.216		−0.008		−0.004	
	(0.053)	0.583	(0.053)	0.583	(0.070)	0.093	(0.070)	0.09	(0.081)	0.011	(0.081)	0.008	(0.108)	0.942	(0.107)	0.968
Constant	−0.092		−0.093		0.787		0.785		0.782		0.766		1.044		1.061	
	(0.095)	0.332	(0.095)	0.330	(0.141)	0.000	(0.142)	0.000	(0.173)	0.000	(0.174)	0.000	(0.194)	0.000	(0.195)	0.000
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	1173		1173		645		645		324		324		315		315	
R2	0.350		0.350		0.163		0.163		0.243		0.251		0.224		0.229	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A9
Robustness test: Controlling for high vs. low innovation-intensive industry.

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.018		0.024		0.057		0.054		0.081		0.109		0.041		−0.018	
	(0.017)	0.283	(0.017)	0.159	(0.016)	0.000	(0.019)	0.006	(0.020)	0.000	(0.022)	0.000	(0.031)	0.193	(0.043)	0.682
Diversified	0.050		0.051		−0.081		−0.082		0.030		0.039		−0.170		−0.180	
	(0.024)	0.036	(0.024)	0.035	(0.042)	0.055	(0.043)	0.060	(0.058)	0.606	(0.060)	0.512	(0.061)	0.005	(0.062)	0.004
Log basic x Diversified			−0.015				0.007				−0.076				0.114	
			(0.033)	0.640			(0.031)	0.823			(0.042)	0.074			(0.053)	0.032
R&D	0.670		0.670		0.141		0.141		0.223		0.221		0.083		0.084	
	(0.024)	0.000	(0.024)	0.000	(0.092)	0.125	(0.092)	0.125	(0.109)	0.041	(0.109)	0.042	(0.172)	0.632	(0.172)	0.625

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Table A9 (*continued*)

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Public	−0.019		−0.020		0.190		0.191		0.140		0.137		0.212		0.220	
	(0.043)	0.654	(0.043)	0.646	(0.050)	0.000	(0.050)	0.000	(0.071)	0.050	(0.069)	0.050	(0.075)	0.005	(0.075)	0.004
Subsidiary	0.012		0.013		−0.043		−0.043		−0.052		−0.051		0.001		0.003	
	(0.031)	0.690	(0.031)	0.686	(0.053)	0.418	(0.053)	0.418	(0.064)	0.414	(0.064)	0.423	(0.076)	0.984	(0.076)	0.972
Startup	0.058		0.059		0.241		0.241		0.303		0.306		0.192		0.191	
	(0.031)	0.063	(0.031)	0.061	(0.076)	0.002	(0.076)	0.002	(0.073)	0.000	(0.073)	0.000	(0.127)	0.131	(0.127)	0.134
Log employees	−0.013		−0.013		0.027		0.027		0.041		0.042		0.020		0.018	
	(0.010)	0.188	(0.010)	0.204	(0.017)	0.102	(0.017)	0.103	(0.021)	0.051	(0.021)	0.047	(0.024)	0.423	(0.024)	0.449
Foreign	−0.055		−0.055		0.144		0.144		0.145		0.145		0.053		0.056	
	(0.048)	0.252	(0.048)	0.247	(0.068)	0.035	(0.068)	0.035	(0.074)	0.051	(0.073)	0.050	(0.109)	0.624	(0.108)	0.605
High inno intense	−0.054		−0.053		0.163		0.163		0.271		0.273		0.057		0.053	
	(0.045)	0.233	(0.045)	0.238	(0.077)	0.033	(0.077)	0.034	(0.085)	0.001	(0.085)	0.001	(0.103)	0.581	(0.103)	0.605
Constant	0.126		0.132		0.350		0.350		0.091		0.085		0.591		0.599	
	(0.064)	0.048	(0.063)	0.036	(0.138)	0.011	(0.138)	0.011	(0.160)	0.571	(0.160)	0.595	(0.217)	0.007	(0.218)	0.006
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	2042		2042		1027		1027		509		509		508		508	
R2	0.459		0.459		0.117		0.117		0.201		0.203		0.108		0.110	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A10
Robustness test: Controlling for year dummies.

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.003		0.005		0.052		0.046		0.067		0.090		0.035		−0.020	
	(0.014)	0.808	(0.017)	0.789	(0.016)	0.001	(0.019)	0.017	(0.018)	0.000	(0.021)	0.000	(0.033)	0.277	(0.043)	0.631
Diversified	0.006		0.006		−0.080		−0.081		0.015		0.022		−0.150		−0.159	
	(0.028)	0.840	(0.029)	0.836	(0.043)	0.062	(0.044)	0.066	(0.060)	0.799	(0.062)	0.717	(0.060)	0.013	(0.062)	0.010
Log basic x Diversified			−0.003				0.013				−0.063				0.110	
			(0.024)	0.894			(0.031)	0.684			(0.039)	0.105			(0.055)	0.046
R&D	0.038		0.038		0.170		0.170		0.219		0.219		0.177		0.179	
	(0.062)	0.534	(0.062)	0.534	(0.084)	0.044	(0.084)	0.044	(0.104)	0.035	(0.104)	0.035	(0.146)	0.227	(0.146)	0.222
Public	−0.086		−0.086		0.188		0.189		0.176		0.173		0.201		0.208	
	(0.049)	0.081	(0.049)	0.081	(0.050)	0.000	(0.050)	0.000	(0.072)	0.014	(0.070)	0.014	(0.073)	0.006	(0.073)	0.004
Subsidiary	−0.020		−0.020		−0.035		−0.035		−0.040		−0.039		−0.022		−0.021	
	(0.037)	0.590	(0.037)	0.591	(0.051)	0.493	(0.051)	0.493	(0.065)	0.540	(0.065)	0.544	(0.076)	0.772	(0.076)	0.785
Startup	0.059		0.059		0.290		0.290		0.265		0.267		0.216		0.216	
	(0.044)	0.180	(0.044)	0.180	(0.071)	0.000	(0.071)	0.000	(0.076)	0.000	(0.076)	0.000	(0.113)	0.057	(0.114)	0.058
Log employees	0.009		0.009		0.030		0.030		0.034		0.034		0.024		0.023	
	(0.010)	0.390	(0.010)	0.389	(0.016)	0.062	(0.016)	0.063	(0.021)	0.104	(0.021)	0.101	(0.023)	0.311	(0.023)	0.330
Foreign	−0.067		−0.067		0.145		0.145		0.150		0.151		0.117		0.121	
	(0.059)	0.256	(0.059)	0.255	(0.065)	0.026	(0.065)	0.026	(0.074)	0.045	(0.074)	0.041	(0.104)	0.262	(0.103)	0.243
i2007	0.050		0.050		0.049		0.049		0.028		0.029		−0.003		−0.003	
	(0.032)	0.126	(0.032)	0.126	(0.050)	0.331	(0.051)	0.334	(0.074)	0.708	(0.074)	0.694	(0.070)	0.961	(0.070)	0.961
i2008	0.024		0.025		0.006		0.006		0.095		0.096		−0.099		−0.100	
	(0.033)	0.459	(0.033)	0.458	(0.050)	0.902	(0.050)	0.904	(0.070)	0.175	(0.070)	0.171	(0.067)	0.139	(0.067)	0.137
Constant	0.809		0.809		0.441		0.442		0.336		0.334		0.539		0.543	
	(0.072)	0.000	(0.072)	0.000	(0.109)	0.000	(0.109)	0.000	(0.140)	0.016	(0.139)	0.017	(0.179)	0.003	(0.179)	0.003
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	1238		1238		1062		1062		532		532		519		519	
R2	0.033		0.033		0.120		0.120		0.201		0.202		0.148		0.151	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A11A
Robustness test: High publication intensive industries.

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	0.029		0.025		0.065		0.059		0.060		0.084		0.062		0.013	
	(0.018)	0.104	(0.023)	0.273	(0.017)	0.000	(0.020)	0.003	(0.022)	0.006	(0.021)	0.000	(0.031)	0.051	(0.044)	0.770
Diversified	0.065		0.064		−0.077		−0.079		0.058		0.074		−0.171		−0.185	
	(0.030)	0.032	(0.031)	0.041	(0.056)	0.172	(0.059)	0.182	(0.079)	0.459	(0.084)	0.380	(0.079)	0.031	(0.083)	0.026
Log basic x Diversified			0.009				0.013				−0.066				0.089	
			(0.031)	0.771			(0.034)	0.709			(0.043)	0.129			(0.055)	0.107
R&D	0.643		0.643		−0.021		−0.021		−0.140		−0.143		0.130		0.129	
	(0.028)	0.000	(0.028)	0.000	(0.126)	0.869	(0.126)	0.870	(0.138)	0.308	(0.138)	0.302	(0.212)	0.539	(0.212)	0.545
Public	−0.047		−0.046		0.151		0.152		0.271		0.271		0.030		0.043	
	(0.059)	0.426	(0.059)	0.433	(0.068)	0.026	(0.068)	0.025	(0.083)	0.001	(0.082)	0.001	(0.110)	0.784	(0.111)	0.698
Subsidiary	0.017		0.017		−0.021		−0.021		−0.078		−0.079		0.038		0.037	
	(0.044)	0.694	(0.044)	0.695	(0.067)	0.759	(0.068)	0.758	(0.087)	0.373	(0.086)	0.363	(0.092)	0.678	(0.092)	0.687
Startup	0.054		0.054		0.219		0.219		0.379		0.383		0.106		0.107	
	(0.038)	0.153	(0.038)	0.154	(0.091)	0.016	(0.091)	0.016	(0.083)	0.000	(0.084)	0.000	(0.156)	0.497	(0.156)	0.491
Log employees	−0.010		−0.010		0.021		0.021		0.026		0.027		0.016		0.015	
	(0.012)	0.390	(0.012)	0.385	(0.021)	0.313	(0.021)	0.318	(0.028)	0.344	(0.028)	0.324	(0.031)	0.600	(0.031)	0.627
Foreign	−0.069		−0.069		0.024		0.024		0.041		0.046		0.009		0.012	
	(0.064)	0.284	(0.064)	0.284	(0.086)	0.779	(0.086)	0.783	(0.122)	0.738	(0.121)	0.706	(0.119)	0.942	(0.118)	0.918
Constant	0.075		0.076		0.547		0.548		0.577		0.569		0.461		0.472	
	(0.042)	0.076	(0.042)	0.073	(0.140)	0.000	(0.141)	0.000	(0.167)	0.001	(0.168)	0.001	(0.228)	0.045	(0.230)	0.041
N	1111		1111		573		573		292		292		275		275	
R^2	0.402		0.402		0.041		0.041		0.082		0.085		0.047		0.050	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A11B
Robustness test: Low publication intensive industries.

									Innovativeness II							
	Innovativeness I				*Innovativeness II*				External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Log basic pubs	−0.003		0.015		0.049		−0.004		0.097		0.079		−0.002		−0.092	
	(0.030)	0.924	(0.022)	0.501	(0.034)	0.149	(0.038)	0.908	(0.025)	0.000	(0.026)	0.003	(0.091)	0.985	(0.075)	0.221
Diversified	0.001		0.002		−0.064		−0.069		−0.028		−0.030		−0.091		−0.100	
	(0.031)	0.984	(0.031)	0.940	(0.062)	0.304	(0.063)	0.274	(0.094)	0.762	(0.095)	0.750	(0.086)	0.289	(0.087)	0.252
Log basic x Diversified			−0.058				0.140				0.043				0.301	
			(0.077)	0.447			(0.063)	0.026			(0.048)	0.362			(0.135)	0.027
R&D	0.666		0.666		0.341		0.340		0.496		0.495		0.248		0.249	
	(0.029)	0.000	(0.029)	0.000	(0.120)	0.005	(0.120)	0.005	(0.101)	0.000	(0.101)	0.000	(0.219)	0.257	(0.220)	0.259
Public	−0.012		−0.011		0.267		0.272		0.092		0.095		0.395		0.403	
	(0.059)	0.844	(0.059)	0.855	(0.063)	0.000	(0.062)	0.000	(0.101)	0.360	(0.101)	0.349	(0.092)	0.000	(0.091)	0.000
Subsidiary	−0.021		−0.022		−0.072		−0.071		−0.088		−0.088		−0.067		−0.062	
	(0.047)	0.652	(0.047)	0.643	(0.082)	0.381	(0.083)	0.390	(0.113)	0.436	(0.113)	0.437	(0.121)	0.581	(0.121)	0.611

(*continued on next page*)

Table A11B (*continued*)

	Innovativeness I				*Innovativeness II*				*Innovativeness II* External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Startup	0.065		0.065		0.230		0.228		0.261		0.260		0.194		0.193	
	(0.040)	0.108	(0.040)	0.106	(0.091)	0.012	(0.091)	0.013	(0.088)	0.003	(0.088)	0.003	(0.155)	0.213	(0.156)	0.217
Log employees	0.000		0.000		0.022		0.022		0.054		0.054		0.002		0.001	
	(0.015)	0.981	(0.015)	0.980	(0.024)	0.368	(0.024)	0.370	(0.037)	0.151	(0.037)	0.151	(0.033)	0.955	(0.033)	0.964
Foreign	0.005		0.004		0.254		0.252		0.351		0.351		0.140		0.133	
	(0.063)	0.934	(0.063)	0.947	(0.087)	0.004	(0.088)	0.004	(0.093)	0.000	(0.093)	0.000	(0.167)	0.403	(0.168)	0.427
Constant	0.046		0.046		0.190		0.192		−0.065		−0.064		0.340		0.344	
	(0.050)	0.357	(0.050)	0.363	(0.145)	0.191	(0.145)	0.186	(0.141)	0.643	(0.141)	0.648	(0.239)	0.156	(0.240)	0.154
N	1113		1113		512		512		247		247		259		259	
R2	0.466		0.466		0.080		0.081		0.133		0.133		0.066		0.070	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

Table A12
Robustness test: Binary measure of basic research based on the strict definition.

	Innovativeness I				*Innovativeness II*				*Innovativeness II* External innovation				Internal innovation			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β		β		β		β		β		β		β		β	
	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*	(SE)	*p*
Basic strict	0.047		0.043		0.148		0.094		0.271		0.378		0.021		−0.162	
	(0.048)	0.324	(0.057)	0.447	(0.060)	0.014	(0.093)	0.312	(0.060)	0.000	(0.089)	0.000	(0.114)	0.854	(0.140)	0.250
Diversified	0.024		0.023		−0.073		−0.078		0.008		0.019		−0.141		−0.157	
	(0.023)	0.308	(0.024)	0.323	(0.043)	0.086	(0.044)	0.078	(0.059)	0.895	(0.063)	0.765	(0.060)	0.019	(0.062)	0.011
Basic x Diversified			0.009				0.113				−0.212				0.415	
			(0.090)	0.923			(0.109)	0.302			(0.120)	0.079			(0.166)	0.013
R&D	0.652		0.652		0.172		0.172		0.222		0.221		0.167		0.169	
	(0.024)	0.000	(0.024)	0.000	(0.084)	0.041	(0.084)	0.041	(0.103)	0.032	(0.103)	0.033	(0.152)	0.273	(0.153)	0.269
Public	−0.020		−0.020		0.188		0.191		0.153		0.143		0.215		0.220	
	(0.041)	0.625	(0.041)	0.627	(0.049)	0.000	(0.049)	0.000	(0.067)	0.022	(0.065)	0.028	(0.076)	0.005	(0.076)	0.004
Subsidiary	−0.013		−0.013		−0.035		−0.034		−0.058		−0.059		−0.008		−0.006	
	(0.033)	0.683	(0.033)	0.684	(0.050)	0.490	(0.050)	0.501	(0.063)	0.364	(0.063)	0.347	(0.078)	0.920	(0.078)	0.934
Startup	0.069		0.069		0.279		0.278		0.262		0.264		0.217		0.217	
	(0.031)	0.025	(0.031)	0.026	(0.069)	0.000	(0.069)	0.000	(0.069)	0.000	(0.069)	0.000	(0.119)	0.070	(0.120)	0.071
Log employees	−0.005		−0.005		0.031		0.030		0.039		0.040		0.024		0.024	
	(0.010)	0.653	(0.010)	0.652	(0.016)	0.058	(0.016)	0.062	(0.021)	0.062	(0.020)	0.054	(0.023)	0.298	(0.023)	0.311
Foreign	−0.022		−0.022		0.132		0.132		0.146		0.145		0.091		0.085	
	(0.046)	0.632	(0.046)	0.632	(0.064)	0.039	(0.064)	0.040	(0.073)	0.046	(0.073)	0.047	(0.105)	0.386	(0.105)	0.418
Constant	0.065		0.065		0.463		0.464		0.348		0.347		0.518		0.525	
	(0.042)	0.126	(0.042)	0.125	(0.105)	0.000	(0.105)	0.000	(0.137)	0.011	(0.136)	0.011	(0.179)	0.004	(0.178)	0.003
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	2224		2224		1085		1085		539		539		534		534	
R2	0.454		0.454		0.119		0.120		0.200		0.202		0.138		0.143	

Notes: *Innovativeness I* is measured by new-to-industry (NTI) versus new-to-firm (NTF) innovations; *Innovativeness II* is measured by substantial distinctiveness from existing offerings (i.e., it is patented or the given innovation had a large implementation gap).

References

Abernathy, W.J., Clark, K.B., 1985. Innovation: mapping the winds of creative destruction. Res. Policy 14 (1), 3–22.

Adner, R., 2006. Match your innovation strategy to your innovation ecosystem. Harv. Bus. Rev. 84 (4), 98.

Aghion, P., Howitt, P., 1998. Capital accumulation and innovation as complementary factors in long-run growth. J. Econ. Growth 3, 111–130.

Aghion, P., Akcigit, U., Howitt, P., 2014. What do we learn from Schumpeterian growth theory?. In: Handbook of Economic Growth, vol. 2. Elsevier, pp. 515–563.

Akcigit, U., Hanley, D., Serrano-Velarde, N., 2021. Back to basics: basic research spillovers, innovation policy, and growth. Rev. Econ. Stud. 88, 1–43.

Anderson, P., Tushman, M., 1990. Technological discontinuities and dominant designs: a cyclical model of technological change. Adm. Sci. Q. 35, 604–633.

Añón Higón, D., 2016. In-house versus external basic research and first-to-market innovations. Res. Policy 45 (4), 816–829. https://doi.org/10.1016/j.respol.2016.01.005.

Argyres, N., Rios, L.A., Silverman, B.S., 2020. Organizational change and the dynamics of innovation: Formal R&D structure and intrafirm inventor networks. Strateg. Manag. J. 41 (11), 2015–2049.
Arora, A., Ceccagnoli, M., 2006. Patent protection, complementary assets, and firms' incentives for technology licensing. Manag. Sci. 52 (2), 293–308.
Arora, A., Gambardella, A., 1994. The changing technology of technical change: general and abstract knowledge and the division of innovative labour. Res. Policy 23, 523–532.
Arora, A., Gambardella, A., 2010. Ideas for rent: an overview of markets for technology. Ind. Corp. Chang. 19 (3), 775–803. https://doi.org/10.1093/icc/dtq022.
Arora, A., Fosfuri, A., Gambardella, A., 2001. Markets for Technology. MIT Press.
Arora, A., Ceccagnoli, M., Cohen, W.M., 2008. R&D and the patent premium. Int. J. Ind. Organ. 26 (5), 1153–1179.
Arora, A., Cohen, W.M., Walsh, J.P., 2016. The acquisition and commercialization of invention in American manufacturing: incidence and impact. Res. Policy 45 (6), 1113–1128. https://doi.org/10.1016/j.respol.2016.02.005.
Arora, A., Belenzon, S., Patacconi, A., 2018. The decline of science in corporate R&D. Strateg. Manag. J. 39, 3–32.
Arora, A., Belenzon, S., Patacconi, A., Suh, J., 2019. Why the U.S. innovation ecosystem is slowing down. In: Harvard Business Review (digital).
Arora, A., Belenzon, S., Patacconi, A., Suh, J., 2020. The changing structure of American innovation: some cautionary remarks for economic growth. Innov. Policy Econ. 20 (1), 39–93.
Arrow, K.J., 1962. Economic welfare and the allocation of resources for invention. In: The Rate and Direction of Inventive Activity: Economic and Social Factors. National Bureau of Economic Research, pp. 609–626. https://EconPapers.repec.org/RePEc:nber:nberch:2144.
Arundel, A., 2001. The relative effectiveness of patents and secrecy for appropriation. Res. Policy 30, 611–624.
Becker, R.A., Gray, W.B., Marvakov, J., 2021. NBER-CES manufacturing industry database (1958-2018, version 2021a) version 2021a. https://www.nber.org/research/data/nber-ces-manufacturing-industry-database.
Cassiman, B., Veugelers, R., 2006. In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition. Manag. Sci. 52 (1), 68–82. http://www.jstor.org/stable/20110484.
Cassiman, B., Veugelers, R., Zuniga, P., 2008. In search of performance effects of (in) direct industry science links. Ind. Corp. Chang. 17 (4), 611–646.
Ceccagnoli, M., Graham, S., Higgins, M., Lee, J., 2010. Productivity and the role of complementary assets in firms' demand for technology innovations. Ind. Corp. Chang. 19 (3), 839–869.
Chesbrough, H., 2003. Open Innovation. Harvard Business School.
Christensen, C., Rosenbloom, R., 1995. Explaining the attacker's advantage: technological paradigms, organizational dynamics, and the value network. Res. Policy 24, 233–257.
Cohen, W., 2010. Fifty years of empirical studies of innovative activity and performance. In: Hall, B., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation, vol. 1. Elsevier, pp. 129–213.
Cohen, W.M., Levinthal, D.A., 1989. Innovation and learning: the two faces of R&D. Econ. J. 99 (September), 569–596.
Cohen, W.C., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm Sci. Q. 35, 128–152.
Cohen, W.M., Nelson, R.R., Walsh, J.P., 2000. Protecting their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not). NBER Working Paper #7552.
Cohen, W.M., Goto, A., Nagata, A., Nelson, R., Walsh, J., 2002. R&D spillovers, patents and the incentives to innovate in Japan and the United States. Res. Policy 31, 1349–1367.
Cohen, W.M., Lee, Y.-N., Walsh, J.P., 2021. How innovative are innovations? A multidimensional, survey-based approach. In: Corrado, C., Haskel, J., Miranda, J., Sichel, D. (Eds.), Measuring and Accounting for Innovation in the 21st Century. University of Chicago Press, pp. 139–182.
Cyert, R.M., March, J.G., 1963. A Behavioral Theory of the Firm. Prentice-Hall.
Dasgupta, P., David, P.A., 1994. Toward a new economics of science. Res. Policy 23, 487–521.
de Rassenfosse, G., Palangkaraya, A., Webster, E., 2016. Why do patents facilitate trade in technology? Testing the disclosure and appropriation effects. Res. Policy 45 (7), 1326–1336. https://doi.org/10.1016/j.respol.2016.03.017.
Dosi, G., 1982. Technological paradigms and technological trajectories. Res. Policy 11, 147–162.
Duguet, E., 2006. Innovation height, spillovers and TFP growth at the firm level: evidence from French manufacturing. Econ. Innov. New Technol. 15 (4–5), 415–442.
Fabrizio, K.R., 2009. Absorptive capacity and the search for innovation. Res. Policy 38 (2), 255–267.
Gambardella, A., 1992. Competitive advantages from in-house scientific research: the US pharmaceutical industry in the 1980s. Res. Policy 21 (5), 391–407.
Gambardella, A., Giuri, P., Luzzi, A., 2007. The market for patents in Europe. Res. Policy 36 (8), 1163–1183. https://doi.org/10.1016/j.respol.2007.07.006.
Gans, J.S., Hsu, D.H., Stern, S., 2008. The impact of uncertainty intellectual property rights on the market for ideas: evidence from patent grant delays. Manag. Sci. 54 (5), 982–997.
Greve, H.R., 2003. A behavioral theory of R&D expenditures and innovations: evidence from shipbuilding. Acad. Manage. J. 46 (6), 685–702. https://doi.org/10.2307/30040661.
Griliches, Z., 1986. Productivity, R&D, and basic research at the firm level in the 1970s. Am. Econ. Rev. 76, 141–154.
Grimpe, C., Hussinger, K., 2014. Pre-empted patents, infringed patents and firms' participation in markets for technology. Res. Policy 43 (3), 543–554. https://doi.org/10.1016/j.respol.2013.12.001.
Haeussler, C., Harhoff, D., Mueller, E., 2014. How patenting informs VC investors–the case of biotechnology. Res. Policy 43 (8), 1286–1298.
Hall, B.H., Lerner, J., 2010. The financing of R&D and innovation. In: Handbook of the Economics of Innovation. Elsevier, pp. 609–639.
Hsu, D.H., Hsu, P.H., Zhao, Q., 2021. Rich on paper? Chinese firms' academic publications, patents, and market value. Res. Policy 50, 104319.
Kalton, G., 1983. Introduction to Survey Sampling. Sage.
Larivière, V., Macaluso, B., Mongeon, P., Siler, K., Sugimoto, C., 2018. Vanishing industries and the rising monopoly of universities in published research. PloS One 13 (8), e0202120.
Laursen, K., 2012. Keep searching and you'll find: what do we know about variety creation through firms' search activities for innovation? Ind. Corp. Chang. 21 (5), 1181–1220.
Laursen, K., Salter, A., 2006. Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. Strateg. Manag. J. 27, 131–150.
Lee, E.S., Forthofer, R.N., Lorimor, R.J., 1989. Analyzing Complex Survey Data. Sage.
Leten, B., Kelchtermans, S., Belderbos, R., 2022. How does basic research improve innovation performance in the world's major pharmaceutical firms? Ind. Innov. 29, 396–424.
MacKenzie, S.B., Podsakoff, P.M., Podsakoff, N.P., 2011. Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques. MIS Q. 35 (2), 293–334. https://doi.org/10.2307/23044045.
Mackey, T.B., Barney, J.B., Dotson, J.P., 2017. Corporate diversification and the value of individual firms: a Bayesian approach, 38 (2), 322–341.
Mairesse, J., Mohnen, P., 2010. Using innovation surveys for econometric analysis. In: Hall, B., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation, vol. 2. North-Holland, pp. 1129–1155.
Malerba, F., McKelvey, M., 2020. Knowledge-intensive innovative entrepreneurship integrating Schumpeter, evolutionary economics, and innovation systems. Small Bus. Econ. 54, 503–522.
Mansury, M.A., Love, J.H., 2008. Innovation, productivity and growth in US business services: a firm-level analysis. Technovation 28 (1–2), 52–62.
Martinez-Senra, A.I., Quintas, M.A., Sartal, A., Vázquez, X.H., 2015. How can firms' basic research turn into product innovation? The role of absorptive capacity and industry appropriability. IEEE-TEM 62 (2), 205–216.
Mowery, D.C., Rosenberg, N., 1989. New developments in U.S. technology policy: implications for competitiveness and international trade policy. Calif. Manage. Rev. 32 (1), 107–124.
Nelson, R.R., 1959. The simple economics of basic scientific research. J. Polit. Econ. 67, 297–306.
OECD and Eurostat (Ed.), 2009. Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data, 3rd ed. OECD and Eurostat.
OECD/Eurostat, 2018. Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation, 4th Edition: The Measurement of Scientific, Technological and Innovation Activities. OECD Publishing. https://doi.org/10.1787/9789264304604-en.
Pavitt, K., 1991. What makes basic research economically useful? Res. Policy 20, 109–119.
Pisano, G.P., 2015. You need an innovation strategy. Harv. Bus. Rev. 93 (6), 44–54.
Rodriguez, M., Doloreux, D., Shearmur, R., 2017. Variety in external knowledge sourcing and innovation novelty: evidence from the KIBS sector in Spain. Technovation 68, 35–43.
Rosenberg, N., 1982. Inside the Black Box: Technology and Economics. Cambridge University Press.
Rosenberg, N., 1990. Why do firms do basic research (with their own money)? Res. Policy 19, 165–174.
Schumpeter, J.A., 1939. Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process. McGraw Hill, Abridged.
Schumpeter, J.A., 1942. Capitalism, Socialism and Democracy. Harper & Brothers.
Simonton, D.K., 2003. Scientific creativity as constrained stochastic behavior: the integration of product, person, and process perspectives. Psychol. Bull. 129 (4), 475.
Stephan, P.E., 2010. The economics of science. In: Handbook of the Economics of Innovation, vol. 1. North-Holland.
Stern, S., 2004. Do scientists pay to be scientists? Manag. Sci. 50 (6), 835–853. https://doi.org/10.1287/mnsc.1040.0241.
Teece, D.J., 1986. Profiting from technological innovation: implications for integration, collaboration, licensing and public policy. Res. Policy 15, 285–305.