Reaching for the stars: When does basic research collaboration between firms and academic star scientists benefit firm invention performance?

Received: 13 November 2020 | Accepted: 25 October 2021

DOI: 10.1111/jpim.12607

JOURNAL OF PRODUCT INNOVATION MANAGEMENT pdma

ORIGINAL ARTICLE

Reaching for the stars: When does basic research collaboration between firms and academic star scientists benefit firm invention performance?

Linde Colen[1] | René Belderbos[2,3,4] | Stijn Kelchtermans[1,2] | Bart Leten[1,2]

[1]Department of Marketing and Strategy, Hasselt University, Hasselt, Belgium

[2]Department of Management, Strategy and Innovation, KU Leuven, Brussels, Belgium

[3]School of Business and Economics, Maastricht University, Maastricht, Netherlands

[4]UNU MERIT, Maastricht, Netherlands

Correspondence
Stijn Kelchtermans, Department of Management, Strategy and Innovation, KU Leuven, Warmoesberg 26, 1000 Brussels, Belgium.
Email: stijn.kelchtermans@kuleuven.be

Funding information
Research foundation - Flanders, Grant/Award Number: 11ZZM15N and G07301N

Associate Editor: Gina O´Connor.

Abstract

While their expertise and scientific excellence make academic star scientists attractive collaboration partners for firms, this study indicates that firms face difficulties in capturing value from collaborations with academic stars. Stars are time constrained, may be less committed to commercialization, and can be a source of undesired knowledge spillovers to other firms. The purpose of this study is to recognize the contingencies under which collaboration with star scientists is positively associated with a firm's ability to produce valuable patents (invention performance). We analyze a panel data set on the collaborations in basic research (publication data) and invention performance (patent output) of 60 prominent pharmaceutical firms. We find that basic research collaboration with academic stars is on average not associated with a performance premium above the overall positive influence of collaborating with academia. We only observe this premium if the star scientist abstains from simultaneous collaboration with other firms (‘dedication’) and extend her collaboration with the firm to involve not only basic but also applied research (‘translation’). Extending prior work that has focused on corporate star scientists, we find that if the collaboration involves an internal firm star scientist, a translational contribution of the academic star is no longer a prerequisite, and may even be detrimental to inventive performance. Our findings inform the literatures on industry-science links and firms’ (scientific) absorptive capacity by revealing the crucial contingencies for firms to benefit from partnering with the best and brightest among academic scientists.

KEYWORDS

knowledge transfer, star scientists, university-industry collaboration

1 | INTRODUCTION

It is well known that the distribution of achievements in scientific research is highly skewed, with a small group of scientists responsible for a disproportional share of research output, in terms of quantity as well as quality (e.g., Azoulay et al., 2014; Lotka, 1926; Rosen, 1981). These star scientists, as leaders within their research field, also act as important nodes in global scientific networks (Luo et al., 1981; Murray, 2004). These characteristics make star scientists interesting hires or collaboration partners for firms in science-based industries involved in intense competition to develop innovative products and technologies. Prior studies have focused attention on the performance benefits that in-house star scientists might bring (Almeida et al., 2011; Hess & Rothaermel, 2011, 2012; Grigoriou & Rothaermel, 2014; Kehoe & Tzabbar, 2013, 2015; Rothaermel & Hess, 2007; Subramanian et al., 2013). However, only a small minority of star scientists is employed by private firms. For instance, Zucker et al. (1998) noted that 98% of the star scientists within the Genbank were affiliated to a university or research institution. Star scientists generally appear reluctant to commit themselves to work in the private sector where restrictive company policies may hamper the freedom to publish and define one's own research agenda (Murray, 2004; Sauermann & Stephan, 2013; Stern, 2004). For many firms this leaves collaboration with star scientists employed by universities (from here on referred to as academic star scientists) as the most common strategy to get access to their skills, network, and expertise.

The rationale behind firms' interest in reaching out to those who are on the scientific frontier is rooted in extant research, which has emphasized the importance of basic research in generating inventions in science-based industries (Arora et al., 2018; Cassiman et al., 2008; Della Malva et al., 2015; Fabrizio, 2009; Fleming & Sorenson, 2004; Gambardella, 1992; Mansfield, 1995, 1998; Rosenberg, 1990). In the context of the pharmaceutical industry, basic research can lead to patented inventions on chemical or biological drug compounds, which can further lead to the commercial introduction of drugs on the market if the compounds prove effective in an elaborate clinical trial process (e.g., Cockburn, 2007; Kola & Landis, 2004). Prior studies have generally shown positive performance effects of (basic) research collaboration with universities (e.g., Almeida et al., 2011; Belderbos et al., 2004, 2016; Cockburn & Henderson, 1998; Fabrizio, 2009). In the particular context of biotechnology, research has shown an important role of (collaborations with) academic star scientists in the formation and success of biotechnology firms (Zucker et al., 1998, 2002).

Despite the importance for firms of joint basic research with universities, it remains unclear whether involving academic star scientists in such collaborative research offers firms greater benefits than collaborating with non-star academics. We argue that achieving an invention premium in collaborating with academics stars in comparison to academic non-stars may not be straightforward. On the one hand, prior literature (Hess & Rothaermel, 2012; Zucker et al., 2002) stressed the benefits for firms from collaborating with academic stars in basic research. Their unique human capital helps deepening firms' fundamental scientific insights, signal firms' scientific excellence and embed their research efforts in the larger scientific community. On the other hand, we posit in this article that firms may also have difficulties in extracting value from collaborating with academic star scientists in basic research. First, star scientists are likely to have a taste for pure and open science, which may conflict with firms' commercialization objectives. Second, given their reputation and academic excellence, and the often-abundant financial resources that come with their status, star scientists have multiple options for industry collaboration (Stephan & Audretsch, 1996) and they may utilize this bargaining power to select and shape collaborations according to their own interests. In particular, when star scientists collaborate with multiple firms, there is an increased risk that knowledge of one collaboration partner spills over to other firms. Third, star scientists' ambitious research agendas and extensive responsibilities may also imply a lack of time and commitment to make substantive contributions to joint research with an industrial partner. Hence, whether collaboration with academic star scientists in basic research is to be preferred over collaboration with other (non-star) academic scientists is likely

Practitioner points

- Intuitively we may expect that collaborating with the very top among academics benefits firms, yet collaborating with these academic star scientists also entails important challenges.
- Organizations seeking to benefit from the extraordinary expertise of academic star scientists should take into account two important conditions:
    - The top academic should be a dedicated collaboration partner, and avoid simultaneous collaboration with other firms.
    - The top academic should not only be involved in basic research but also in applied research collaboration with the firm, enhancing her ability to assist the firm in the translation of research into a marketable product.
- When the firm also employs a star scientist who is engaged in the collaborative research with an academic star scientist, the translation of the joint research is better performed by the internally employed star scientists instead of the academic star scientist.

to depend on how such collaborations are arranged to address potential incongruences with the invention objectives of the firm.

The current study examines the conditions under which collaboration with academic star scientists in basic research is associated with an invention premium for the firm in comparison to collaboration with academic non-star scientists. By invention premium we refer to the invention performance effects of star collaboration over and above the average performance effects of collaboration with non-stars. We argue that three conditions may be of particular relevance. First, the benefits of collaboration may depend on whether the star has a dedicated relationship with the focal firm and abstains from simultaneous collaboration with other firms. Dedication is likely to increase commitment and trust building (Coleman, 1988; Colyvas et al., 2002; Granovetter, 1985) while limiting risks of knowledge spillovers to potential rival firms (Gianiodis et al., 2016). Second, the benefits of collaboration may be greater if the firm can collaborate with the academic star scientist not only in basic research but also in applied research, aiding the translation of basic research findings (Agrawal, 2006) into valuable inventions. Finally, as collaborating firms may employ internal star scientists, involvement of these scientists in collaborative research with academic stars may also be related to the success of the collaboration. In particular, we expect that involving internal stars, with their deep knowledge of firms' invention needs provide the firm with a high level scientific absorptive capacity (e.g., Belderbos et al., 2016; Melnychuk et al., 2021) to collaborate effectively with external stars, and will benefit the firm in particular if a collaboration with the academic star scientist is lacking a translational (applied research) dimension. If translation becomes the sole responsibility of the internal star scientist, knowledge redundancies (Hess & Rothaermel, 2011) and potential conflicts due to ill-defined roles (Cattani et al., 2013; Groysberg et al., 2011) in collaboration with academic stars may be reduced and invention performance enhanced.

Empirically, we analyze a panel data set (1995–2002) containing detailed information on patents and scientific publications of 60 of the most prominent American, European, and Japanese firms in the pharmaceutical industry. We use information on co-publications in basic and applied research journals to measure collaborations between firms and academic star scientists and identify star scientists as leaders in their scientific field both in terms of publication and citation performance. We estimate pseudo-fixed effects models relating citation-weighted patent performance to firms' prior engagement in academic star collaborations under different contingencies, while controlling for a range of relevant firm, star, and star-firm collaborative project characteristics. To guide hypothesis development, the quantitative analysis is informed by extant literature and a series of interviews with eight academic star scientists and five firm R&D managers conducted in 2014–2016. The academic star scientists had their residence in Belgium, collaborated with industry, and received a European Research Council (ERC) grant within the life sciences. The R&D managers were employed in five large pharmaceutical firms in our sample (Johnson & Johnson, GSK, Novartis, UCB and Ajinomoto) and were closely involved in relationship management of their firm with university partners.

Our study contributes to the literature streams on firms' engagement with star scientists (Almeida et al., 2011; Hess & Rothaermel, 2011, 2012; Grigoriou & Rothaermel, 2014; Kehoe & Tzabbar, 2015, 2015; Rothaermel & Hess, 2007; Subramanian et al., 2013), on the importance of basic research for firm invention (Arora et al., 2018; Cassiman et al., 2008; Della Malva et al., 2015; Fabrizio, 2009; Fleming & Sorenson, 2004; Gambardella, 1992; Mansfield, 1995, 1998; Rosenberg, 1990), on industry-science linkages through collaborative research (Almeida et al., 2011; Belderbos et al., 2004; Cockburn & Henderson, 1998; Fabrizio, 2009), and the literature on firms' (scientific) absorptive capacity (Belderbos et al., 2016; Cassiman & Veugelers, 2006; Cohen & Levinthal, 1990).

2 | THEORETICAL BACKGROUND AND HYPOTHESES

2.1 | Basic research and collaborations with academia

Basic research is an important driver of invention in science-based industries (Mansfield, 1998; Narin et al., 1997). Firms search for fundamental insights to conduct well-informed experiments and to identify promising research directions (Cassiman et al., 2008; Rosenberg, 1990). Numerous studies have shown the importance of basic research in improving firms' invention performance (Belderbos et al., forthcoming; Cockburn & Henderson, 1998; Fleming & Sorenson, 2004; Gambardella, 1992). Prior research has also suggested that the benefits of performing basic research are greater when it is conducted in collaboration with universities (Cockburn & Henderson, 1998; Fabrizio, 2009; Zucker et al., 2002). As firms find it difficult to remain up-to-date with all scientific advances, firms turn to university partners to provide guidance and scientific expertise in research areas relevant to the firm (Cassiman & Veugelers, 2006). Firms' engagement of academic scientists in their invention activities comes in various guises such as collaborative research, contract research, consulting and informal relationships (Perkmann et al., 2013). In this study, we focus on the modalities that govern *collaborative research* and, in line with prior research, we measure it through firm-academia co-publications.

While firms may endeavor to do joint basic research with academic stars, such university-industry collaborations face numerous obstacles. The defining characteristics of academic science, such as the rapid disclosure and wide dissemination of research results as well as the recognition-based reward system, are different from the performance goals and incentive systems in firms (Arora & Gambardella, 1994). The contrasting views that academia and industry have on science can lead to conflicting research goals and priorities for joint research projects (Bruneel et al., 2010; Dasgupta & David, 1994; Tartari et al., 2012). Collaborations in basic research in this regard pose particular difficulties, as they require close interaction and understanding to transfer tacit and complex knowledge across organizations (Bruneel et al., 2010; Plewa et al., 2013; Tartari et al., 2012). The high levels of uncertainty that are defining basic research, combined with difficult-to-monitor knowledge generation and transfer, rule out complete contracting to govern basic research collaborations. Instead, trust and mutual interdependence are crucial (Faems et al., 2008).

2.2 | The value and challenges of collaborative basic research with academic star scientists

Among university-industry collaborations, academic star scientists may be particularly attractive research partners because of their extraordinary human and social capital. The benefits embodied by the collaborating star scientist may accrue to the firm in several ways. First, stars may convey valuable tacit knowledge beyond what is codified in journal articles (Arora & Gambardella, 1990; Cockburn & Henderson, 1998) and they may disclose preliminary research results, on which collaborating firms can build their own applied research, faster than rival firms can without access to the star (Fabrizio, 2009). Second, given the expertise and deep knowledge of the academic star scientist, collaboration may be instrumental to enhance the quality of firms' basic research and their understanding of the relevant technological landscape (Gambardella, 1992), helping them in the selection of fruitful research avenues, thus avoiding costly research trials (Fabrizio, 2009; Fleming & Sorenson, 2004; Rosenberg, 1990). Third, interaction with academic star scientists can enhance the research capabilities of firms' R&D departments, not only by helping them to interpret results of internal research (Rosenberg, 1990) but also to identify and understand the results and implications of externally conducted basic research (Cockburn & Henderson, 1998; Gambardella, 1992). Fourth, academic star scientists occupy central positions in international research networks and have large networks of research partners (Hess & Rothaermel, 2012) which can be activated in collaborations with firms. These benefits of working with academic stars are not restricted to any given collaboration but affect the effectiveness of basic research at the level of the firm (Della Malva et al., 2015).

Collaboration with star scientists also poses significant challenges. These include the aforementioned challenges common to all firm–university collaborations: overcoming the differences in work practices and incentives, achieving trust between the partners, and dealing with potential knowledge spillovers to other firms given the public good characteristics of knowledge. Firms' collaborations with star scientists are likely to face additional difficulties. A first relevant characteristic of such collaborations is the stronger independence of academic star scientists relative to nonstars. Star scientists tend to have good access to support from funding agencies and collaboration partners from academia and industry, and are less likely to depend on a single collaboration partner for funding their research. Hence, they can be more selective in choosing their research partners (Stephan & Audretsch, 1996) and will be better able to negotiate collaboration contracts that meet their own interests. One of the interviewed star scientists illustrates this:

> They [firms] can collaborate with us if they are interested, and if they are not, then we will just proceed with other partners, if necessary.

One of the interviewed R&D managers confirmed the difficulty of attracting star scientists for industrial collaboration:

> Big names can be quite demanding and have got high expectations. [...] Sometimes it's much more pleasant to work with young and upcoming professors who haven't made their name yet, but are very open and eager to work with others.

Second, star scientists often take up additional managerial responsibilities and tasks in addition to their broad research portfolio, limiting available time to perform collaborative research with firms. In the life sciences, star scientists often manage large research laboratories (Woolston, 2016), involving responsibilities such as funding acquisition and people management. Furthermore, star scientists are often involved in editorial work for journals and frequently attend international conferences. The time pressure resulting from these broader responsibilities may force star scientists to limit their efforts and commitment to collaborative research, which may harm the contribution to the inventive performance of the collaborating firm.

These hurdles characterizing firms' collaboration in basic research with academic star scientists are likely to imply important contingencies for firms to realize an invention premium from collaboration. Inspired by insights from the literature and our interviews with star scientists and R&D managers, we argue that firms can increase the invention benefits accruing from these collaborations by engaging in a "dedicated" collaboration—where the star scientist abstains from simultaneous collaboration with other firms—and "translational" collaboration—where the research collaboration is not limited to basic research but also includes applied research. We use the term "translational research" to refer to the commonly used 'bench-to-the-bedside' interpretation,[1] describing a process in which basic research, through follow-up applied research (e.g., on effectiveness, dosage, transportation inside the human body, etc.) produces new drugs for patients. Finally, we argue that the co-involvement of internal star scientists in collaborative research with academic star scientists is less likely to benefit the firm if the collaboration with the academic star scientist is lacking a translational (applied research) dimension.

2.3 | Dedicated collaboration with the academic star

A dedicated collaboration, with the focal firm being the only industrial research partner of the academic star scientist, may alleviate a number of concerns and difficulties pertaining to collaborative research with academic star scientists. These arguments relate to the threat of knowledge spillovers, the time constraints academic star scientists face, and trust building.

First, an important issue a firm has to deal with when working with academic scientists, is the partial public good nature of scientific knowledge (Arrow, 1962; Nelson, 1959). While the development of scientific knowledge requires significant investments, knowledge spillovers can lead to competitors' free riding on these investments at limited learning costs. Moreover, these learning costs drop considerably with proximity to the scientist possessing such knowledge (Zucker et al., 2002). Hence, rival firms engaged in parallel research with the same academic star scientist may experience significantly lower learning costs, and may pose a serious threat to the collaborating firm in the race to establish patented inventions. Even contractual limitations on sharing certain pieces of knowledge developed in collaboration with a star may not completely avoid knowledge from spilling over, since the transfer of knowledge—in particular if it is tacit in nature—is hard to monitor and, consequently, contract breaches are hard to legally enforce. The interviewed R&D managers recognized the risk of knowledge spillovers:

> It's sometimes a very thin line to know which information scientists really need to have and how far do you go in sharing information. It's finding the right balance to create trust and have a very collaborative environment in which you can both operate and exchange information, but not going beyond what is essential for both parties to do what they're supposed to be doing and not turn them into a competitor.
>
> You have to assess very carefully what that person's level of involvement with a competitor is.

If the university star scientist solely collaborates with the focal firm, this may considerably limit the probability of knowledge spilling over to competing firms—accidentally or due to opportunistic behavior by the academic scientist (Gianiodis et al., 2016)—as there is no parallel knowledge exchange with other firms. Even if other firms face only temporarily restricted access to the academic star scientist this may help the focal firm to gain a competitive advantage in patent and drug development races. Without direct interactions with the academic star scientist, other firms are less likely to obtain the tacit knowledge to put the results of basic research to productive use in new inventions (Arora & Gambardella, 1990; Cohen & Levinthal, 1990). Similarly, the dedicated star scientist will be less restricted in her communication with the scientists of the focal-collaborating firm as she is not hindered by secrecy agreements stemming from other projects, and there is less need to worry about inadvertently disclosing confidential information across collaborations.

A second hurdle to successful firm-academic star collaboration is the independence of star scientists and the alternative opportunities they have to pursue research and to get funding. Star scientists can be selective when choosing research partners and make strong demands during negotiations. They may negotiate collaborative contracts that put an upper bound on the time they invest in the collaboration, or they may economize on time invested once the collaboration is in place. An

[1]This definition is commonly used in both the biomedical scientific literature (e.g., Woolf, 2008) and in industry (e.g., "*Translational research is the fusion of basic lab work and the clinic*"—Dr. Thompson, CEO of Oncolytics Biotech, cited in PharmaVOICE, 2014).

interviewed star scientist expressed this tendency to economize on time:

> Well, my preference would be the least amount of face-time. I mean, frequent meetings chew up a vast amount of my week and having to attend an extra meeting or a regular meeting would be a negative.

The competition for a star's time was also raised by an interviewed R&D manager:

> If they're very busy and collaborating with a lot of others there will be time constraints.

Time constraints are likely to make it more difficult for a firm to engage in frequent and profound interactions with the star scientist that are conducive to successful collaboration. While collaborations among academic partners tend to be more flexible and informal, collaboration with industrial partners is often subject to strict planning and time management with contractually determined deadlines and milestones (Du et al., 2014). Hence, if the star scientist has multiple industrial collaboration partners competing for her attention, it will be more difficult to devote sufficient time to each partner, which may reduce learning effects and collaboration benefits for the firms.

Finally, dedicated collaborative relationships are more likely to be characterized by improved knowledge sharing and trust. Firms that enjoy dedicated access to a star scientist are likely to commit more strongly to the relationship (Colyvas et al., 2002) and invest in relationship-specific assets (e.g., Elfenbein & Lerner, 2012) due to the privileged access and associated better knowledge appropriation prospects. The increased availability and commitment of both the star scientist and the firm, and the reduced concerns about unwanted knowledge disclosures, may lead to stronger interpersonal relationships and the buildup of trust, mutual understanding, and goodwill (Coleman, 1988; Granovetter, 1985). Strong social relationships in turn enhance the depth of knowledge sharing and the effectiveness of research collaborations (Bruneel et al., 2010; Plewa et al., 2013; Tartari et al., 2012).

The above arguments suggest that, taken as a whole, dedication may mitigate problems associated with academic star collaboration and strengthen potential benefits.

Hypothesis 1 (Dedication) *The invention premium a firm may reap from basic research collaborations with academic star scientists relative to working with non-stars is positively associated with the degree to which these collaborations involve dedicated stars (i.e., star scientists with no other industrial collaboration partner than the focal firm).*

2.4 | Translation: Extending basic research collaboration to applied research

A key challenge for firms is the ‘translation’ of basic research to applied research focusing on successful technology development. Applied research benefits from tacit knowledge related to the basic research process, such as the trial and error process that has led to scientific findings, which is relevant information to establish critical conditions for successful experiments (Agrawal, 2006; Fuller & Rothaermel, 2012; Sorenson et al., 2006). Knowledge on the basic research process resides in the minds of the discovering scientists who have an information advantage toward others in implementing this knowledge into successful inventions (Jensen & Thursby, 2001). As the translation process is highly uncertain, it is impossible to determine in advance when and what knowledge a firm may need during applied research. It will therefore be important for firms to stay in close contact with the discovering academic star scientists to discuss solutions if applied research faces obstacles. One of the interviewed star scientists referred to his deep understanding of the invention process as a reason to remain involved during applied research:

> [we may remain involved in applied research because] we are sometimes the experts who are more knowledgeable on how something works, how the drug should be developed. From their side, they [the corporate scientists] are of course the experts in technically realizing the development. In the best case, this is accomplished in collaboration.

The interviewed R&D managers also referred to the benefits of involving academic star scientists in both basic and applied research:

> The academic partner may have some very deep, fundamental knowledge about something and we understand the development process better. There is a mutual enrichment at work here. I would say in the long run it's good to keep the originating principal investigator on board as long as possible. It might be that certain questions in applied research actually can be addressed with the basic research know-how that a person has.[2]

[2]There is evidence that biopharmaceutical firms increasingly rely on partnerships with academia not only to identify promising pathways for novel drugs through basic research, but also to guide their translation into clinical development of medical products (Milne & Malins, 2012).

In general, firms face the problem that excellence in basic science does not automatically imply valuable invention. The criteria of what constitutes good academic research and what defines a good invention are not the same (Foray & Lissoni, 2010; Gittelman & Kogut, 2003). Academic star scientists who engage in both basic and applied research with a focal firm get acquainted with both perspectives and develop competences to recognize opportunities in basic research that are worth to pursue further by the focal firm. Although star scientists differ in their 'taste' for applied research and commercialization (Sauermann & Roach, 2012; Sauermann & Stephan, 2013; Stokes, 1997) some stars are willing to engage in collaborative applied research, as this may provide valuable feedback for their basic research and allows them to see their research materialize in actual inventions (Rosenberg, 1990; Sauermann & Roach, 2014). The latter motivation is illustrated by a quote from a star scientist, Prof. Dr. Carmeliet, winner of the Ernst Jung Prize in medicine (Oncurious, 2015):

> Working with [biotech firm] Oncurious gives me the occasion to remain very closely involved in the process of developing a drug for clinical use.

The above arguments suggest that an academic star scientist who can span the basic-applied boundary within collaborative research can align her expertise in basic research with the development practices and invention needs of the firm. Hence, basic science collaboration is more likely to be associated with a positive invention performance premium for the firm if the collaboration extends to applied research:

Hypothesis 2 (Translation) *The invention performance premium a firm may reap from basic research collaborations with academic star scientists relative to working with non-stars is positively associated with the degree to which these collaborations are translational (i.e., the star scientists are also involved in applied research collaboration with the focal firm).*

2.5 | Involving internal star scientists in academic star collaboration

Prior studies have reported both positive (Almeida et al., 2011; Subramanian et al., 2013), negative (Zucker et al., 2002), and insignificant (Hess & Rothaermelm, 2011, 2012; Rothaermel & Hess, 2007) effects of internally employed star scientists on firms' invention performance. We complement this prior work on the general performance implications of internal star scientists by examining whether the involvement of internal star scientists in collaborative basic research with academic stars affects the contingencies under which academic star scientist collaboration is expected to be associated with a performance premium. There are both positive and negative influences to be expected of involving internal star scientists in basic research collaboration with external academic star scientists.

On the one hand, having a star scientist on both sides of the partnership may enhance collaborative performance. First, the balance in terms of scientific excellence by involving an internal star may improve the understanding and absorption of the knowledge and expertise that the external star brings to the table, leading to more effective communication and collaboration. The internal star with her expertise can serve as a form of high-level scientific absorptive capacity (e.g., Belderbos et al., 2016, 2017; Cassiman & Veugelers, 2006; Melnychuk et al., 2021) required to work with the best and brightest in science. This is especially the case when knowledge is characterized by a high level of tacitness and knowledge transfer requires close personal interactions (Zucker et al., 2002).

Second, considering the social circles within academia, top scientists might be more likely to connect and interact, be it formally or informally, with other top scientists. Such prior interaction is known to enhance trust and psychological safety which facilitates coordination (Cattani et al., 2013; Huckman et al., 2009; Reagans et al., 2005; Salas et al., 2018) and stimulates knowledge-sharing (Bercovitz & Feldman, 2011; Bruneel et al., 2010; Huckman et al., 2009; Plewa et al., 2013; Salas et al., 2018; Tartari et al., 2012), especially of sensitive information and creative thoughts. Even without prior interaction, the solid scientific reputation of both the internal and academic star scientists is also likely to increase mutual trust and respect, which stimulates knowledge-sharing and communication. The interviewed academic star scientists and R&D managers experienced these communication benefits:

> There are a couple of key advantages [of working with an internal star scientist]. One is they speak the same language. [...] [Second,] they also understand more of your [the academic star's] motivations and what it is that you want out of a collaboration.

> [Collaborating with a star scientist within the company] turns a one way interaction into a two way interaction.

> They [the academic star scientist and the internal scientists] need to understand each

> other well. That is why we [the company] have an expert talking to a university expert.

On the other hand, involving internal star scientists in collaborative research with academic star scientists may also result in knowledge redundancy or, in the worst case, conflict. First, academic star scientists possess the research expertise and access to the academic community that internal star scientists can also bring to a research collaboration. Hence, both types of star scientists can be considered as substitutive sources of knowledge in a collaboration (Hess & Rothaermel, 2011; Subramanian et al., 2013) and the marginal benefit of an academic star scientist may be smaller if an internal star is also involved. More so, when the stars are socially linked, not only are they likely to share the same knowledge, they are also likely to share the same perspectives, potentially reducing creativity during collaborative interactions (Dan et al., 2008; Granovetter, 1983). Second, accommodating top performers within the same team may lead to inefficiency and even conflict (e.g., Cattani et al., 2013; Groysberg et al., 2011) for instance about allocation of resources (Prato & Ferraro, 2018). Teams tend to benefit from some hierarchy and clear roles, as this brings clarity to social interaction, assigns accountability for task accomplishment and sets rules for the distribution of resources within the team. In teams with more than one star, a clear hierarchy is missing and egos may get in the way of decision-making and knowledge-sharing (Groysberg et al., 2011). During the interviews, the importance of complementarity in skills and knowledge was brought forward:

> If we [academic star scientists] look for a collaboration partner within a company then I would more likely search for someone who can make the difference within the company instead of someone with a similar profile.

> If we [the academic star scientist and the internal scientist] would have the same knowledge and skills, there would be no need for a collaboration. […] It is the lack of knowledge and skills that forms the basis of collaboration, otherwise you can do it yourself.

The arguments above do not suggest an unambiguous effect of internal star scientist involvement in collaborative research with academic star scientists, but we argue that joint involvement of internal and external stars is likely to be less beneficial if it involves applied research. An internal star scientist is familiar not only with what needs to happen to be successful in drug development but also with the firm's precise research approach, which puts her in a good position to take up the role of translating basic research from 'the bench' to 'the bedside'. The presence of an internal star in the collaboration then only results in a clear task division if the academic star scientist's involvement remains limited to basic research, for which her added value is undisputed and for which the match with an internal star may actually be beneficial in terms of shared scientific understanding and trust building. Conversely, involving both an internal and academic star in the subsequent translational step is more prone to lead to conflicts due to the combination of two high-status scientists, with the academic star stepping onto the internal star's turf. In other words, if the collaboration includes an internal star, the benefits of involving an academic star in translational activities (as proposed in Hypothesis 2) are less likely to hold. We hypothesize:

Hypothesis 3 (translation and internal star involvement) *The positive association between translational collaboration and the invention premium the firm may reap from collaborations with academic star scientists relative to working with non-stars under Hypothesis 2 is weaker when these collaborations involve internal stars.*

3 | DATA, VARIABLES, AND METHODS

We test our hypotheses by relating the invention performance of pharmaceutical firms to their past (collaborative) basic research activities and the characteristics of such collaborations. Collaboration may stimulate invention performance not only directly through the development of collaboration-specific patents based on the collaborative research, but also through more general knowledge transfer and learning from collaboration, affecting the broader R&D invention portfolio of the firm (e.g., Cassiman et al., 2008). Hence, the (full) effects of (star) scientist collaboration are best captured by invention at the firm level, and we take this as our level of analysis.

Firms select academic stars to collaborate with, and stars select firms. The selection process underlying star-firm collaboration of various types may lead to different invention outcomes due to the specific characteristics of the academic star, firm, and collaborative project, and this may bias inferences on the role of the hypothesized contingencies. We address this by estimating elaborate models controlling for a range of firm characteristics, star characteristics, and characteristics of the collaborative research projects of firms and stars that are likely to be relevant in the selection process and may affect invention performance. In particular, the analysis controls for prior star-firm experience in collaboration, which may influence selection and may at the same time improve the effectiveness of collaboration, and an indicator of the quality of the star-firm collaborative projects, which could be associated with the choice for specific collaboration types. In a supplementary analysis, we also examine the robustness of our findings when controlling for particular characteristics of a firm and its academic partner that may make matches more productive (Banal-Estañol et al., 2018; Mindruta, 2013). Although our detailed analyses do not suggest that heterogeneity in project quality or patterns of matching between firms and star scientists play a role as confounders, the difficulty in finding suitable instruments for the set of focal variables precludes us from interpreting our findings as causal relationships. We interpret the partial correlations as associations.

3.1 | Data

We constructed a panel data set on the patent and publication activities of 60 of the most prominent pharmaceutical firms in the world from 1995 to 2002. The firms have headquarters in the United States, Europe, or Japan and are the largest R&D spenders (in absolute terms) in the pharmaceutical industry as reported in the 2004 EU Industrial R&D Investment Scoreboard. This ranking lists the top 500 corporate R&D investors based in Europe, and the top 500 companies based outside Europe (mainly in the US and Japan), in 2003. A list of the sample firms is provided in the Appendix. We rely on an unbalanced panel data set of 406 observations in our empirical analyses, as some sample firms were only created after 1995 (e.g., Novartis was formed as a result of a merger of Ciba-Geigy and Sandoz in 1996) and due to some missing values for R&D expenses.

The characteristics of research by the major players in the pharmaceutical industry makes this a particularly interesting context for investigating academic star-firm collaborations. The science-based nature of research in the pharmaceutical industry and the high patenting and publication rates allow examining research collaboration processes and outcomes through quantitative analysis. The major pharmaceutical companies are involved in the entire process from basic to applied research (Campbell, 2005), with the interplay between basic and applied research being an important aspect of firm performance. Finally, the ongoing debate on the productivity crisis in the pharmaceutical sector (e.g., Rafols et al., 2014) calls for deeper insights on the characteristics of effective research (collaboration) strategies.

3.2 | Invention performance: Patent data

Following related work (e.g., Rothaermel & Hess, 2007; Zucker et al., 2002), we utilize patent data to measure firms' invention performance. Patent data are extracted from the PATSTAT database (2011 update), which contains information on patents from all major patent offices worldwide. Patents are a good indicator in our context as the propensity to patent inventions is high in the pharmaceutical industry (Arundel & Kabla, 1998). We weigh patent counts by the number of forward patent citations to control for differences in the economic value of patents (Gambardella et al., 2008; Hall et al., 2005; Trajtenberg, 1990). We consider citation-weighted patent counts as a reflection of (collaborative) research success, before other capabilities of the firm related to brand management, distribution, advertising, pricing etc. come in. We note that patents are only awarded if there is convincing evidence of industrial applicability, and forward citations to patents in the pharmaceutical industry are associated with a chemical or biological compound being tested (successfully) in clinical trials. Research (Chiou et al., 2016) on molecular entities indicates a strong correlation between the citation rate of pharmaceutical patents and the successful introduction of drugs based on these patents. Hence, there are also arguments to consider the citation-weighted patent counts as an indicator of innovation performance, and prior work using this measure also adopted such a terminology (e.g., Belderbos et al., 2016; Cloodt et al., 2006; Kaiser et al., 2018). In the current article, we use the term invention and invention performance, as it is closest to the actual measure used. The citation-weighted patent count is based on a fixed 4-year window of forward citations to establish a comparable citation window across patents (Hall et al., 2005; Trajtenberg, 1990). For the calculation of citation counts, both the citing and cited patents are integrated at the DOCDB PATSTAT patent family level to avoid double counting patents on similar inventions (Martinez, 2011).

Patent data are collected at the consolidated parent firm level by searching for patents under the name of the parent firm as well as all their majority-owned subsidiaries. For this purpose, yearly lists of companies' subsidiaries were used, as reported in corporate annual reports, yearly 10-K reports filed with the SEC in the US, and, for Japanese firms, information on foreign subsidiaries published by Toyo Keizai in the yearly 'Directories of Japanese Overseas Investments'. Acquired firms and their patent stocks are considered part of a parent firm from the year the acquisition transaction was completed.

3.3 | Basic research: Publication data

We draw on information contained in publication data on pharmaceutical research in the PubMed database to construct indicators of firms' research activity and collaborative behavior. Publication counts are strong and timely indicators of firms' levels of involvement in research in science-based industries (Arora & Gambardella, 1990; Gambardella, 1992) since the turn-around time of publications in life sciences is typically only a few months (Kaplan et al., 2003). As with patent data, publication data are also collected at the consolidated firm level. We relate invention (citation-weighted patent) performance of firms to (collaborative) basic research activity in the past 4 years (t–4 to t–1). This time window is likely to be sufficient, as most patents are applied for relatively early in the drug discovery phase (Campbell, 2005). Since we are interested in firms' collaborative basic research focusing on compound (drug) discovery we use the CHI journal classification scheme to distinguish applied research (levels 1 and 2) from basic research (levels 3 and 4) (Hamilton, 2003; Thursby & Tursby, 2011).

3.4 | Collaboration with (star) academics: Co-publications

We draw on information from co-publications to build collaboration measures for the sample firms (Cockburn & Henderson, 1998; Fabrizio, 2009). We identify academic co-authorship by a string-matching algorithm that recognizes affiliations of universities or research institutions. Prior research has validated co-publications as a reliable indicator of collaborative research (Cockburn & Henderson, 1998; Fabrizio, 2009). Most collaborations result in co-authored publications (Melin & Persson, 1996), and most co-publications do reflect actual research collaborations (Hicks et al., 1996).

Among the academic co-publications of firms, we identify collaborations with academic star scientists. We draw on disambiguated author names in the Authority data set of Torvik and colleagues (Torvik et al., 2005; Torvik & Smalheiser, 2009), which has uniquely identified authors on PubMed publications. The authors of the firm (co-)publications can be compared with all authors within PubMed on the basis of their complete publication records. We follow the definition of Rothaermel and Hess (2007) and identify star scientists as those authors whose publication and citation performance are both three standard deviations above the means in their scientific field. We apply the criterion in a dynamic manner, using a moving 4-year window to allow for changes in star scientist status due to retirement or career changes (e.g., Groysberg & Nanda, 2004; Groysberg et al., 2008). Star scientist status is assessed per scientific field to control for discipline-specific publication and citation patterns (e.g., Kelchtermans & Veugelers, 2013). Based on the journal categorization of Thomson Reuters in 2014, we consider 44 distinct fields in the scientific domains "Medicine" and "Life Sciences". If the scientist has, in at least one of these fields, publication and citation counts that both exceed the aforementioned threshold she is considered a star scientist. Since the arguments for hypothesis three hinge upon internal and academic stars being of comparable status, we apply the same threshold for both groups.

In total, from among 2,478,517 scientists with at least one publication in PubMed in the broader fields of "Medicine" or "Life Sciences", we identified 26,586 (1.1%) star scientists. For the sample firms, among the 126,325 authors listed on their basic research publications, 7340 (5.8%) were identified as stars. This set of star scientists consists of both scientists employed internally by the firms and those employed by a research institution or university. To identify star scientists working in academia we applied specific string-matching algorithms on three types of affiliation data: first-author addresses, email-addresses (Torvik et al., 2005; Torvik & Smalheiser, 2009) and addresses listed on the corresponding Web of Science publications of the PubMed publications. In line with previous studies (e.g., Zucker et al., 1998), we find that most star scientists listed on the publications of the sample firms are academics (6554 or 89%). Among the 60 firms in the sample, 34 firms also employ internal star scientists, who author a total of 7681 basic research publications. Of these, 2172 are in collaboration with an academic star scientist. The sample firms' basic research collaborations with academic star scientists not involving internal stars is about six times that number (13,622). Our measure of collaboration with academic star scientists includes both collaboration with an individual star scientist working at a university, and collaboration through a research consortium or a funded research center to which the star scientist is affiliated.

An academic star-firm basic research collaboration is considered "*translational*" if the collaboration not only includes joint basic research but if the star scientist has also published applied research in collaboration with the focal firm in the same 4-year window. An academic star-firm collaboration is categorized as "*dedicated*" if the star scientist is not mentioned as co-author on any publication (basic or applied) of another (bio) pharmaceutical firm during the observation period of 4 years. We consider the 60 largest R&D-spending pharmaceutical firms in the sample in addition to 76 of the largest R&D-spending biotechnology firms in 2004 as the relevant players within the (bio) pharmaceutical industry to determine whether a star is "dedicated" to a single focal firm.

As dedication and translation are not mutually exclusive characteristics of collaboration, we identify four types of collaboration with academic stars: dedicated and translational, dedicated and non-translational, non-dedicated and translational, and non-dedicated and non-translational. The set-up with four exclusive categories provides the most detailed insights into the performance effects of different configurations of dedicated and translational collaborative research, allowing the disentanglement their individual influences. We furthermore distinguish combinations of these four collaboration types with or without the involvement of internal stars, such that we arrive at eight exclusive categories of academic star collaborations in our full regression model.

The construction and descriptive statistics of the collaboration variables are shown in Figure 1. About 58% of firms' basic research publications are co-authored with academics. On average, a quarter of these collaborative basic research publications are co-authored by an academic star, while about three percent of these publications involve only internal stars. Non-star collaborations form the majority of basic research collaborations with academia (72%). Among the collaborations involving academic stars, about 8% also involve internal stars. If we further disentangle these two categories of academic star collaborations, we see that in case of involvement of academic stars only, the collaboration type 'non-dedicated and non-translational' is the most common (60.1%), followed by dedicated and non-translational (23.8%), non-dedicated and translational (10.9%), and dedicated and translational (5%). For academic star collaborations also involving internal stars, the shares of the four types of collaborations are broadly comparable, although the share of dedicated translational collaborations is higher at roughly 10%.

3.5 | Empirical model and variables

We opt for count data models as they take into account the non-negativity and discreteness of our dependent variable: firms' citation weighted patent count. We estimate quasi-maximum likelihood Poisson models that are robust to over-dispersion and against distributional misspecification (Cameron & Trivedi, 2009). To control for time-invariant heterogeneity across firms that is not captured by the model variables, we estimate pseudo-fixed effects models by including the pre-sample average of the dependent variable. The advantage of the pseudo-fixed model is that it does not require strict exogeneity of the error terms, as is the case for conventional fixed effects models (Blundell et al., 1995), provides consistent estimates, and preserves degrees of freedom. The pseudo-fixed effect is measured as the natural logarithm of the firms' patents five to eight years before the start of the observation period. This relatively long pre-sample period avoids convolution with the explanatory variables in the model, such as the basic research collaborations measured one to four years prior to the first observation on invention performance.

In order to identify the relationships under study limiting multicollinearity concerns, while controlling for other key research characteristics of the firm, we employ a cascaded model setup. Firms' resources spent on *R&D*, which should have a direct relationship with invention output, enter in absolute terms. The impact of *in-house basic research* is subsequently included as the ratio of the number of basic research publications in the previous four years over R&D expenditures, while the general effect of performing such *basic research jointly with academia* is measured by the ratio of collaborative to all basic research publications of the firm. The focal variables indicating academic star-firm collaborations under various contingencies are subsequently included as shares of basic research collaborations with academia (as illustrated by Figure 1), with collaboration with academic non-star scientists as the reference group. Hence, the focal variables on collaboration types measure the 'invention premium' of collaborating with stars under various contingencies compared to the average effect of collaborating with non-star academic researchers, as formulated in our hypotheses.

3.6 | Control variables

The models include a range of control variables at the firm, academic star, and firm-star collaboration level to isolate the effects of star collaboration and its contingencies. Besides R&D, basic research, and collaboration with academia in basic research, we include a control for the *technological diversity of a firm's technology portfolio*, which in prior research has been shown to relate in a non-linear way to firms' invention performance (e.g., Leten et al., 2007). Technological diversity is measured as the inverse Herfindahl index of the distribution of the four-year prior patent portfolio over 3-digit IPC patent classes. To allow for a non-linear relationship, this variable is included in both linear and quadratic form. The analysis also controls for the number of *inter-firm research alliances* and associated inter-firm knowledge transfers (e.g., Belderbos et al., 2016; Hess & Rothaermel, 2011; Mowery et al., 1996; Owen-Smith & Powell, 2004) during the past four years (taken from the SDC Platinum database), scaled by R&D expenditures

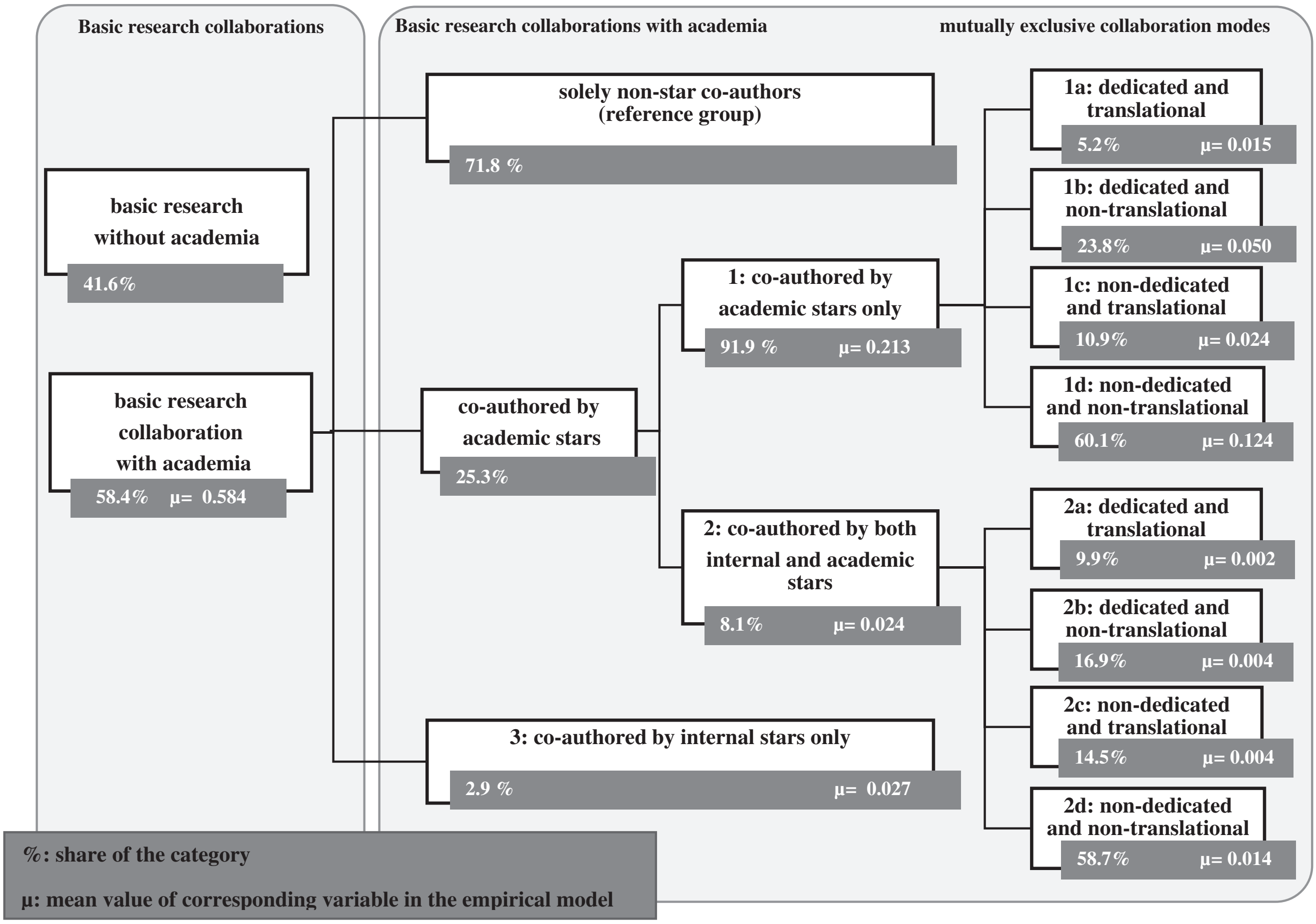

FIGURE 1 Construction and descriptive statistics of the collaboration variables

in the previous year. Further, we include a dummy variable indicating if the firm employs an *internal star scientist* (Hess & Rothaermel, 2011; Zucker et al., 2002). We also include two additional academic research characteristics of the firm that may relate to invention performance: the *quality of the firm's research* (measured by the average yearly citation weighted number of publications in the prior four years), and the *firm's research diversity* (the Blau index of the distribution of publications across the 44 scientific fields within Medicine and Life sciences during the previous four years). Finally, we control for *firm age* as a firm variable that may affect invention performance (e.g., Soh & Subramanian, 2014). Firm age is calculated as the first year that a patent filing of the firm is recorded.

Two other control variables incorporate characteristics of the collaborating academic stars, to take into account possible residual heterogeneity among these extraordinary scientists. While our study focuses on partnerships with scientists in the upper tail of the quality and productivity distribution, there may still be *star scientist* heterogeneity influencing collaborative invention performance outcomes. We include the *research quality* (the average yearly citation weighted number of publications in the prior four years) and the *research diversity* of the collaborating stars' during the previous four years (the Blau index of the distribution of publications across 44 scientific fields during the previous four years).

The analysis also includes two key characteristics at the star-firm collaboration level. First, firms and stars may select the ex-ante most promising projects for collaboration and star scientists might be more willing to take on a specific collaboration configuration if the expected (scientific) impact of the collaborative project is promising. To control for this potential influence of heterogeneous *project quality*, the model includes the average forward citation rate of the collaborative publications. Second, new firm-star collaborations may be partially driven by prior collaborative research and such experience may have positive performance implications. Empirical studies have found a positive relationship between team performance and prior team interaction (Huckman et al., 2009) or prior social links between team members (Bercovitz & Feldman, 2011). At the same time, negative repercussions have also been reported (Dan et al., 2008; Salas et al., 2018), as repeated interaction may limit the amount of new information that can be obtained through collaboration. We include in the models a measure of prior collaborative firm-star experience: the average number of co-publications of the focal firm and the collaborating academic stars in the four-year period prior to the period of the focal star-firm collaborations.[3] Finally, in addition to the *pseudo-fixed firm effects*, all models include *year-fixed effects* to control for time-specific shocks.

Table 1 reports descriptive statistics. Almost all sample firms (55 out of 60) collaborated at least once with an academic star scientist during the sample period. Most of these firms (53) engaged in the most common type of academic star-firm collaboration: non-dedicated and non-translational collaboration with the academic star and not involving internal stars. Even the least frequent collaboration type, dedicated and translational, is still practiced by 39 of the sample firms if this collaboration does not involve internal stars. In contrast, if internal stars are involved, only 13 firms have dedicated translational star collaborations. Of the 32 firms that employ internal star scientists, 29 involve them at least once in collaborations with academic stars.

Table 2 contains the correlation matrix. There is no evident multicollinearity concern regarding the focal variables that are simultaneously included in the empirical models. A relatively high correlation is observed between R&D expenditures and the firm-level pseudo-fixed effect, which is related to the relatively stable R&D budgets of firms over time.

4 | EMPIRICAL RESULTS

Table 3 reports the regression results. Model 1 is the baseline model including only the control variables. In addition to the significant pseudo-firm fixed effect ($p < 0.000$), firms that invest more in R&D ($p < 0.000$), that collaborate more frequently with academia in basic research ($p = 0.003$) and that have a higher research quality ($p = 0.034$) have a higher invention performance. Firms' research and technological diversity show no significant association with invention performance at conventional ($p < 0.05$) significance levels. Firm age appears positively related to invention performance ($p = 0.001$ in model 3), although only slightly in models 1 ($p = 0.090$) and 2 ($p = 0.101$). The academic star controls (research quality and research diversity) have significantly negative and positive coefficients, respectively, but this significance disappears in the full specification of model 3. The quality of collaborative research with star scientists is positive and significantly associated with invention performance ($p = 0.009$) in all models, while prior collaboration experience is also positive and significant in models 2 and 3.

Model 2 includes the share of co-publications in basic research with academic stars. The insignificant coefficient ($p = 0.141$) suggests that on average, star collaboration is not associated with an invention performance premium over and above the positive influence of collaborating with academia. This overall effect warrants further investigation of the potential heterogeneities in the performance benefits of collaboration with academic star scientists, as hypothesized.

Model 3 includes the variables representing the shares of the eight specific collaboration types to examine the contingencies under which academic star scientist collaboration may be associated with a performance premium. There are marked differences between the coefficients of the shares of different collaboration types. For basic research collaborations with academic stars but without internal stars (coefficients β_1), there is a positive and significant coefficient ($p < 0.000$) for dedicated and translational collaboration (β_{1a}) and a negative and significant coefficient ($p = 0.001$) for non-dedicated and non-translational collaboration (β_{1a}). Among the four shares of collaborations that involve both academic and internal star scientists (β_2), the only positive share ($p = 0.010$) is for dedicated and non-translational academic star collaboration (β_{2b}), while significantly negative coefficients ($p < 0.000$) are observed for the two non-dedicated collaboration categories (β_{2c}, β_{2d}).

In order to test our hypotheses, we conduct chi-squared tests (reported in Table 4) on sums of coefficients that capture a given collaboration mode. The sum of coefficients of the shares of dedicated academic star scientist collaboration is higher than the sum of coefficients of the shares of non-dedicated collaboration ($\chi^2 = 14.82$, $p < 0.000$), indicating that there is a beneficial influence of dedication. This confirms hypothesis 1. A test comparing coefficients of collaboration shares with and without a translational component also indicates a statistically significant difference ($\chi^2 = 9.63$, $p = 0.002$), but indicates that the involvement of the star in translation is negatively associated with invention performance, rejecting hypothesis 2. In order to test for Hypothesis 3, we examine the consequences of involving internal star scientists in academic star-assisted translational research (collaborations extending to applied research). Specifically, the test is whether the difference between the coefficients of translational and non-translational collaboration is greater for collaborations not involving internal stars than for collaborations that do involve internal stars. The test shows that

[3] We note that we are not able to control for the geographic location or geographic proximity of collaborating stars, because the Pubmed database does not contain the 1-on-1 correspondence between authors and affiliations.

TABLE 1 Descriptive statistics (406 observations)

	Name	Mean	SD	Min.	Max.	# firms with value >0
Dependent variable						
1	Citation weighted patent count$_t$	644.63	893.91	0	4551	60
Key variables						
2	Log (R&D$_{t-1,\text{ in million USD}}$)	5.22	1.69	0.20	8.49	60
3	Basic research publications$_{t-4\text{ to }t-1}$/ R&D$_{t-1,\text{ in Million USD}}$	0.77	0.98	0.00	11.89	59
4	Basic research co-publ. with academia$_{t-4\text{ to }t-1}$/Basic research publications$_{t-4\text{ to }t-1}$	0.55	0.21	0.00	1.00	57
	Share of basic research co-publications with academia$_{t-4\text{ to }t-1}$					
5	... with academic stars	0.24	0.16	0.00	1.00	55
	... without internal stars and with academic stars	0.21	0.14	0.00	1.00	55
6	... which are dedicated and translational	0.02	0.06	0.00	1.00	39
7	... which are dedicated and non-translational	0.05	0.05	0.00	0.33	47
8	... which are non-dedicated and translational	0.02	0.04	0.00	0.25	43
9	... which are non-dedicated and non-translational	0.12	0.09	0.00	0.57	53
	...with internal stars and with academic stars	0.02	0.05	0.00	0.25	29
10	... which are dedicated and translational	0.00	0.01	0.00	0.05	13
11	... which are dedicated and non-translational	0.00	0.01	0.00	0.09	20
12	... which are non-dedicated and translational	0.00	0.01	0.00	0.14	20
13	... which are non-dedicated and non-translational	0.01	0.03	0.00	0.16	27
14	...with internal stars and without academic stars	0.03	0.07	0.00	0.25	32
Firm controls						
15	Technological diversity$_{t-4\text{ to }t-1,\text{ IPC3}}$	6.87	3.04	0.00	19.15	60
16	Research alliances$_{t-4\text{ to }t-1}$/ R&D$_{t-1,\text{ in million USD}}$	0.04	0.10	0.00	1.43	54
17	Presence of internal star$_{t-4\text{ to }t-1}$	0.54	0.50	0.00	1.00	32
18	Log (firm age)	3.82	0.71	0.00	4.67	60
19	Firm research quality$_{t-4\text{ to }t-1}$	309.67	62.04	0.00	345.18	59
20	Firm research diversity$_{t-4\text{ to }t-1}$	0.28	0.08	0.00	0.37	59
Academic star controls						
21	Research quality of academic stars$_{t-4\text{ to }t-1}$	94.58	65.07	0.00	276.20	55
22	Research diversity of academic stars$_{t-4\text{ to }t-1}$	0.43	0.21	0.00	0.73	55
Star-firm collaboration controls						
23	Quality of basic collaboration with academic stars$_{t-4\text{ to }t-1}$	0.64	0.61	0.00	4.36	53

TABLE 1 (Continued)

	Name	Mean	SD	Min.	Max.	# firms with value >0
24	Collaborative experience firm and academic stars$_{t-4\text{ to }t-1}$	0.60	1.81	0.00	17.31	46
Firm pseudo-fixed effect						
	Firm pseudo-fixed effect	4.70	1.92	0.00	8.44	59

the association between invention performance and translational collaboration is stronger ($\chi^2 = 15.33$, $p = 0.000$) for collaborations without internal stars, confirming hypothesis 3.

Hypothesis 2 was rejected, suggesting that there is no overall positive association between firms' invention performance and translational collaboration with academic stars. However, the difference in the role of translational collaborations with and without internal star involvement (H3) may suggest that a positive association may hold after all, but only for the subset of collaborations without internal stars. A test on the coefficients of collaboration shares with and without translation but not involving internal stars does show that translational collaboration has a stronger ($\chi^2 = 6.17$, $p = 0.013$) positive association with invention performance than non-translational collaboration (Table 4). Conversely, a similar test for collaboration shares involving internal stars shows a significantly negative difference between the coefficients of translational versus non-translational collaboration ($\chi^2 = 13.22$, $p = 0.000$). Hence, once we condition on the presence of internal stars, we find qualified support for hypothesis 2, i.e., there *is* a positive association between invention performance and the degree to which academic star collaborations extend to applied research, but only if these collaborations do not involve internal stars. These conditional tests also help to better understand the results of the test for Hypothesis 3. In particular, they show that the benefit from involving academic stars in applied research is material, but disappears and is even reversed once these collaborations involve internal stars.

It is important to examine the economic significance of the estimation results. Exponentiated coefficients in the negative binomial model can be interpreted as pseudo-elasticities (incidence ratios). We infer that a standard deviation increase in the share of translational and dedicated star collaborations not involving internal stars is associated with a 14-percent increase in invention performance. In contrast, increasing the share of non-translational and non-dedicated star collaborations not involving internal stars by a standard deviation is associated with a 22% decrease in performance. For collaborations involving internal stars, the coefficients suggests an 8% increase in performance (dedicated non-translational), and a decrease of 11% and 14% (non-dedicated translational and non-dedicated non-translational, respectively). However, these effects have to be assessed against the background of a simultaneous and sizeable positive effect of collaboration in basic research with academics, where a standard deviation increase is associated with a performance increase of 19%.

Is collaboration with academic stars in basic research by the sample firms overall positively associated with firm invention performance? This question rises given the observed negative influences of specific types of academic star scientist collaboration, in conjunction with the positive influence of academic collaboration in basic research in general. Simulations at the firm level show that for about 9% of firm-year observations (43 of 460), the particular configuration of basic research collaboration with academic stars is negatively associated with invention performance, although this negative association only shows statistical significance ($p < 0.05$) for two observations. In contrast, for around 71% of firm-year observations (287 out of 406), academic collaboration has a positive association with performance; while for 168 of these observations this association is statistically significant ($p < 0.05$). These findings suggest that while academic star scientist collaboration in basic research under unfavorable contingencies may lead to significantly negative performance premiums compared to non-star collaboration with academia, there is no evidence for an overall negative association between academic star scientist collaboration and firm invention performance. At the same time, under favorable contingencies the results suggest clear positive effects of academic star scientist collaboration.

4.1 | Supplementary analysis

We performed a number of supplementary analyses to examine the robustness of our findings. We briefly summarize the tests and outcomes here. First, we examined the robustness of our findings if we controlled for prior collaboration experience specifically of the team of internal and academic stars, measured as the degree to which prior firm-star collaborations also involved such internal stars. We did not find an additional significant effect for the internal-academic star collaboration experience, and

TABLE 2 Correlation matrix of all variables (406 observations)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.
1.	1.00																						
2.	**0.70**	1.00																					
3.	−0.07	**−0.17**	1.00																				
4.	0.07	0.03	**0.13**	1.00																			
5.	**0.33**	**0.58**	0.08	**0.16**	1.00																		
6.	0.05	−0.10	**0.15**	**0.12**	**0.37**	1.00																	
7.	**0.28**	**0.38**	0.05	**0.13**	**0.52**	−0.03	1.00																
8.	**0.21**	**0.37**	−0.01	0.03	**0.44**	0.06	**0.11**	1.00															
9.	**0.13**	**0.44**	−0.04	**0.11**	**0.71**	−0.07	**0.21**	**0.14**	1.00														
10.	**0.27**	**0.31**	0.00	0.02	**0.29**	**0.12**	**0.10**	**0.19**	0.05	1.00													
11.	**0.34**	**0.37**	0.11	−0.07	**0.32**	0.00	**0.19**	0.06	0.06	**0.23**	1.00												
12.	0.06	**0.20**	**0.10**	−0.02	**0.35**	0.01	**0.15**	**0.29**	0.10	**0.20**	**0.23**	1.00											
13.	0.26	0.41	0.05	−0.00	**0.42**	0.00	**0.11**	**0.12**	**0.12**	**0.33**	**0.57**	**0.27**	1.00										
14.	**0.15**	**0.21**	0.03	−0.03	**0.13**	0.04	0.01	0.08	−0.04	**0.19**	**0.33**	**0.13**	**0.38**	1.00									
15.	**0.27**	**0.39**	**0.18**	**0.21**	**0.33**	0.02	**0.26**	**0.15**	**0.26**	−0.00	**0.22**	**0.10**	0.09	0.01	1.00								
16.	**−0.15**	**−0.32**	0.02	0.04	**−0.15**	**0.27**	**−0.16**	**−0.16**	**−0.22**	−0.06	−0.07	−0.07	−0.09	−0.07	**−0.10**	1.00							
17.	**0.45**	**0.68**	0.01	**−0.10**	**0.51**	0.01	**0.31**	**0.29**	**0.33**	**0.26**	**0.36**	**0.25**	**0.39**	**0.33**	**0.27**	**−0.23**	1.00						
18.	**0.56**	**0.69**	**0.13**	**0.16**	**0.46**	−0.03	**0.27**	**0.25**	**0.35**	**0.24**	**0.26**	**0.16**	**0.34**	**0.17**	**0.37**	**−0.30**	**0.51**	1.00					
19.	**0.14**	**0.33**	**0.15**	**0.52**	**0.30**	0.05	**0.18**	**0.15**	**0.27**	0.05	0.06	0.05	0.08	0.07	**0.31**	−0.08	**0.21**	**0.37**	1.00				
20.	**0.13**	**0.27**	**0.13**	**0.45**	**0.31**	0.06	0.06	**0.21**	**0.34**	0.02	−0.05	0.06	0.03	0.02	**0.22**	**−0.11**	**0.12**	**0.32**	**0.74**	1.00			
21.	**0.31**	**0.62**	0.08	0.07	**0.68**	−0.01	**0.34**	**0.25**	**0.62**	**0.25**	**0.27**	**0.30**	**0.43**	**0.12**	**0.36**	**−0.25**	**0.50**	**0.50**	**0.27**	**0.21**	1.00		
22.	**0.27**	**0.59**	0.09	**0.20**	**0.72**	0.07	**0.42**	**0.31**	**0.65**	**0.13**	**0.21**	**0.17**	**0.26**	**0.12**	**0.43**	**−0.27**	**0.49**	**0.54**	**0.39**	**0.33**	**0.76**	1.00	
23.	**0.36**	**0.53**	0.01	0.04	**0.50**	0.01	**0.26**	**0.17**	**0.43**	**0.23**	**0.25**	**0.17**	**0.32**	**0.11**	**0.29**	**−0.19**	**0.36**	**0.46**	**0.20**	**0.19**	**0.69**	**0.52**	1.00
24.	**0.15**	**0.26**	0.06	0.03	**0.40**	0.06	0.09	**0.31**	**0.16**	**0.52**	**0.27**	**0.59**	**0.44**	**0.16**	0.08	−0.08	**0.24**	**0.20**	0.07	**0.15**	**0.37**	**0.19**	**0.26**

Notes: correlations in bold are significant at 0.05 level. Variables in gray-colored cells are not jointly included in the empirical models. The variable numbers correspond to those in Table 1.

adding this variable had no material effect on the main variables of interest. Second, the emerging literature on matching in research collaborations has suggested that particular matches between the capabilities of a firm and its academic partner may be more productive (Banal-Estañol et al., 2018; Mindruta, 2013). Expansion of the model to include such matching characteristics—positive assortative matching on research quality and basic research orientation; negative assortative matching on research diversity—did not indicate that these influences play an additional role, while the focal results remained unchanged.

Third, we estimated expansions of our model including eight project quality variables, one for each type of star-firm collaboration, and eight prior experience variables, with no qualitative impact on the influence of the focal variables.[4] Fourth, we have expanded our model with a variable measuring the (average) opportunities for research in the domains in which the focal firm collaborates with stars. Opportunities are measured by the worldwide growth in publications in the 44 scientific domains that we also use to identify stars. Adding this variable did not produce significant results, while the core results remained unchanged. Fifth, we added a measure of the collaborative network size of academic stars to our model, measured as the average of the total number of co-authors of the academic stars in the Authority data set (Torvik et al., 2005; Torvik & Smalheiser, 2009). No significant effect was found for the collaborative network size of stars, and core results were unaffected.

Sixth, we addressed the concern that our co-publication variables may partly pick up scientists' mobility between universities and firms rather than collaborative research, and that this may be disproportionally the case for dedicated collaboration. We identified as a possible indicator of such mobility the co-publications in which the number of affiliations is larger than the number of authors, which represent cases of multiple affiliations of at least one of the authors, and possibly but not necessarily, the academic star. Multiple affiliations may occur if a star moves from academia to the firm, keeping (perhaps temporarily) her university affiliation on her publications. This applied to close to four percent of the firm collaborations with academic stars. These multiple affiliations were not more prevalent for star collaborations with dedication: no significant differences could be observed between dedicated and non-dedicated star collaborations in its occurrence (with means of 3.74% and 3.89% respectively, and the p value of the difference at 0.57). Finally, employing an extended eight-year citation window to measure patent quality, rather than a four-year window, did not produce any notable differences in the empirical results. Finally, leaving out the three firms that did not collaborate with star scientists during the observation period and/or that did not engage in basic research also produced similar results.

[4]The only exception concerned the test for a premium of translational collaboration in case no internal stars are involved, which turned insignificant in the specification with eight experience variables.

5 | CONCLUSION AND DISCUSSION

Our analysis of the relationship between pharmaceutical firms' invention performance and their basic research collaborations with academic star scientists revealed that such collaborations on average are not associated with an invention performance premium compared to academic collaborations not involving stars. This finding is surprising, certainly against the backdrop of prior literature (Zucker et al., 2002) that has stressed the benefits for firms of working with the best and brightest academic scientists. Working with academic star scientists does however not only provide advantages to firms, but may face important obstacles related to the full agenda and stronger independence of the star—which may lead to reduced commitment and interaction, a lesser emphasis on translation, and undesired knowledge spillovers to other firms.

Our findings highlight that it is crucial for firms to manage collaborations with academic star scientists by creating the right conditions for increased invention performance, although firms may not always be in a position to demand such conditions. We find that dedication and translation jointly are key conditions to observe an invention performance premium of academic star collaboration in comparison with non-star collaboration—provided that no internal star scientists are involved. Dedication (the academic star abstains from collaboration with other firms) promotes commitment and trust and reduces the threat of knowledge dissipation to other firms. Translation (the collaboration with the academic star in basic research extends to applied research) is important to fruitfully apply insights from basic research to applied research trajectories.

If the basic research collaboration with an academic star also involves an internal star scientist, applied research involvement of the academic star is not required, and can even turn out to be detrimental for a performance premium, presumably because the internal star can fulfill this translational role. Only one configuration of basic research collaboration involving both internal and academic star scientists is associated with a performance premium, namely a

TABLE 3 Academic star collaboration in basic research and firms' invention performance: Pseudo-fixed effects poisson panel regression results

		Model 1		Model 2		Model 3	
		Coef.	*z-value (p-value)*	Coef.	*z*-value (*p*-value)	Coef.	*z*-value (*p*-value)
Key variables							
Log (R&D)		0.23	3.66 (0.000)	0.24	3.88 (0.000)	0.19	3.15 (0.002)
Basic research publications/R&D		0.04	0.85 (0.398)	0.05	0.96 (0.335)	0.03	0.52 (0.601)
Basic research co-publications with academia/Basic research publications		1.06	3.00 (0.003)	1.06	3.02 (0.002)	0.83	2.45 (0.014)
Share of basic research co-publications with academia							
... without internal star and without academic stars		Reference group					
... with academic stars				−0.59	−1.47 (0.141)		
... without internal stars and with academic stars							
... which are dedicated and translational	β_{1a}					2.12	3.58 (0.000)
... which are dedicated and non-translational	β_{1b}					1.30	1.51 (0.132)
... which are non-dedicated and translational	β_{1c}					0.46	0.44 (0.662)
... which are non-dedicated and non-translational	β_{1d}					−2.17	−3.18 (0.001)
... with internal stars and with academic stars							
... which are dedicated and translational	β_{2a}					−6.21	−1.71 (0.086)
... which are dedicated and non-translational	β_{2b}					8.07	2.59 (0.010)
... which are non-dedicated and translational	β_{2c}					−10.26	−4.13 (0.000)
... which are non-dedicated and non-translational	β_{2d}					−4.45	−4.02 (0.000)
... with internal stars and without academic stars						−0.11	−0.17 (0.867)
Firm controls							
Technological diversity		−0.01	−0.15 (0.879)	−0.02	−0.19 (0.852)	0.00	0.00 (0.999)
Technological diversity^2		0.00	−0.44 (0.659)	0.00	−0.41 (0.679)	0.00	−0.59 (0.554)
Research alliances/R&D		0.50	0.84 (0.403)	0.50	0.79 (0.428)	0.23	0.52 (0.603)
Presence of internal star		0.02	0.2 (0.838)	0.07	0.63 (0.528)	0.13	1.13 (0.257)

TABLE 3 (Continued)

	Model 1		Model 2		Model 3	
	Coef.	*z-value (p-value)*	Coef.	*z*-value (*p*-value)	Coef.	*z*-value (*p*-value)
Log (firm age)	0.18	1.7 (0.090)	0.17	1.64 (0.101)	0.34	3.30 (0.001)
Firm research quality	−0.01	−2.12 (0.034)	−0.01	−2.09 (0.037)	−0.01	−2.34 (0.019)
Firm research diversity	1.73	0.52 (0.607)	1.72	0.51 (0.610)	2.87	0.87 (0.386)
Academic star controls						
Research quality of academic stars	0.00	−4.88 (0.000)	0.00	−4.32 (0.000)	0.00	−1.47 (0.142)
Research diversity of academic stars	0.95	2.55 (0.011)	1.06	2.85 (0.004)	0.55	1.33 (0.183)
Star-firm collaboration controls						
Quality of basic collaborations with academic stars	0.17	2.61 (0.009)	0.17	2.62 (0.009)	0.17	2.91 (0.004)
Collaborative experience of firm and academic stars	0.01	1.42 (0.156)	0.02	2.07 (0.039)	0.05	3.53 (0.000)
Pseudo firm-fixed effects and year dummies						
Pseudo firm-fixed effects	0.58	10.77 (0.000)	0.58	10.79 (0.000)	0.54	10.56 (0.000)
Year dummies	Yes		Yes		Yes	
Constant	1.89	3.73 (0.000)	1.9	3.74 (0.000)	1.68	3.43 (0.001)
Log likelihood	−31,484.56		−31,349.61		−26,995.97	
LR test improved model fit (vs. Model 1)			2758.03	(0.000)	8977.18	(0.000)

Notes: All models have 406 observations. *p*-value of robust standard errors in parentheses.

TABLE 4 Tests for the hypotheses on invention performance benefits due to research collaboration with academic stars

	Coefficients	χ^2 (Prob > χ^2)	Answer
Hypothesis 1 Are performance benefits greater in case of dedicated collaboration?			
$\beta_{1a} + \beta_{1b} + \beta_{2a} + \beta_{2b} - \beta_{1c} - \beta_{1d} - \beta_{2c} - \beta_{2d} = 0$	(2.12) + (1.30) + (−6.21) + (8.07) − (0.46) − (−2.17) − (−10.26) − (−4.45) = 21.70	14.82 (0.000)	Yes
Hypothesis 2 Are performance benefits greater in the case of translational collaboration?			
Across all star collaboration modes: $\beta_{1a} + \beta_{1c} + \beta_{2a} + \beta_{2c} - \beta_{1b} - \beta_{1d} - \beta_{2b} - \beta_{2d} = 0$	(2.12) + (0.46) + (−6.21) + (−10.26) − (1.30) − (−2.17) − (8.07) − (−4.45) = −16.64	9.63 (0.002)	No (reduced benefit)
Star collaboration modes not involving internal stars: $\beta_{1a} + \beta_{1c} - \beta_{1b} - \beta_{1d} = 0$	(2.12) + (0.46) − (1.30) − (−2.17) = 3.45	6.17 (0.013)	Yes
Star collaboration modes involving internal stars: $\beta_{2a} + \beta_{2c} - \beta_{2b} - \beta_{2d} = 0$	(−6.21) + (−10.26) − (8.07) − (−4.45) = −16.67	13.22 (0.000)	No (reduced benefit)
Hypothesis 3 Are performance benefits of translational collaboration greater when academic star collaboration does not involve internal stars?			
$\beta 1_a + \beta_{1c} - \beta_{1b} - \beta_{1d} - (\beta_{2a} - \beta_{2c} + \beta_{2b} + \beta_{2d}) = 0$	(2.12) + (0.46) − (1.30) − (−2.17) − (−6.21) − (−10.26) + (8.07) + (−4.45) = 20.12	15.33 (0.000)	Yes

collaboration in which academic stars are dedicated but not involved in applied collaborative research. The lack of more general invention performance benefits in case of joint involvement of internal and academic stars may indicate problems related to knowledge redundancy, hierarchy and conflicts, with non-dedicated collaboration furthermore increasing the risk of knowledge dissipation. Overall, the observed patterns indicate that dedication is the most crucial condition to safeguard the invention returns of collaborations in basic research with academic star scientists, with positive influences regardless of the involvement of internal stars.

Our study emphasizes the difficulty of transferring and safeguarding knowledge in the context of university-industry collaboration, the connected roles of basic and applied research, and the specific role of internal star scientists for invention performance. In doing so, our research contributes to both the broad stream of research on collaboration between firms and academia and the literatures on the role of firms' engagement with (in-house) star scientists and basic research. Few studies in the literature on industry-science collaboration have investigated contingencies of the collaboration-performance relation (Bogers et al., 2017) and paid attention to the role of the collaborating scientists. Our work addresses this gap by suggesting the importance of dedication and translation as crucial contingencies for firms to achieve an invention premium when collaborating with academic star scientists compared to non-stars in basic research. The importance of *dedication* has implications for our understanding of the organization of knowledge networks that span the institutional boundary between academia and industry. More specifically, linkages among organizations have been conceptualized on a continuum between 'closed conduits' where only the linked entities benefit from the exchanged knowledge, and 'porous channels' that allow for knowledge spillovers to external entities (Owen-Smith & Powell, 2004). We find that dedicated collaborations with academic star scientists—reflecting the aforementioned 'closed conduits' rather than 'porous channels'—result in an invention advantage for firms. The fact that firms benefit more from partnering with academic stars who are not embedded in a large network of collaborations with other firms contrasts with extant literature (e.g., Ahuja, 2000) that has emphasized the benefits of integration of firms' research into large networks through their collaboration partners. The importance of *translation* is consistent with the notion in the literature of the role of 'Pasteur' or 'bridging' scientists (Baba et al., 2009; Gittelman & Kogut, 2003; Subramanian et al., 2013) as important collaboration partners of firms. However, our study suggests an important nuance, as the role of translational academic star scientists depends on whether such translational capabilities are available among collaborating in-house star scientists. Results of our study also confirm the importance of in-house basic research for firms' invention performance, in particular when it involves collaboration with academia (Arora et al., 2018; Cassiman et al., 2008; Fabrizio, 2009; Fleming & Sorenson, 2004; Gambardella, 1992) and star academics under certain conditions.

Our study contributes new insights to the literature on firms' absorptive capacity (e.g., Cassiman & Veugelers, 2006; Cohen & Levinthal, 1990). Our work on internal star scientists with their deep knowledge of scientific discovery can be regarded as a special case of firms' absorptive capacity, namely to work effectively with external academic stars. We argue that it is 'scientific absorptive capacity' (e.g., Belderbos et al., 2016, 2017; Melnychuk et al., 2021) that is required to benefit from star collaboration. This absorptive capacity is only built up with investments in in-house scientific research and employing internal (star) scientists. Yet having in-house the same caliber of star scientists as an indicator of absorptive capacity does not necessarily improve firm performance. In order to capitalize on their internal stars in collaborations with external stars, firms need to take into account their characteristics, deal with issues like trust and status, and avoid extending collaborations to translational research. While absorptive capacity in extant literature tends to be conceptualized in rather abstract, knowledge-related terms (Cassiman & Veugelers, 2006; Cohen & Levinthal, 1990), we show that, next to the knowledge dimension, there is also an important behavioral aspect to absorptive capacity if it concerns teaming up with star scientists. We suggest that this behavioral dimension receive more attention in future research.

Our study also contributes to the debate on the role of internal star scientists by highlighting that when they are involved in collaborations with academic stars, a specific configuration of the collaboration is required to bring out benefits. Our study provides a first analysis of the interactive roles of internal and academic star scientists, which have been examined only separately in prior work (e.g., Almeida et al., 2011; Grigoriou & Rothaermel, 2014; Hess & Rothaermel, 2011, 2012; Kehoe & Tzabbar, 2015, 2015; Rothaermel & Hess, 2007; Zucker et al., 2002). Our findings show that this interplay is of importance, as the internal star scientist seems able, and is possibly even more capable than the academic star, to take up the translational role within an academic star-firm collaboration in basic research. Our findings confirm the notion that internal and external star scientists can be considered as substitutive sources of knowledge (Hess & Rothaermel, 2011; Subramanian et al., 2013), leading to underperformance of collaboration. Whereas prior studies focusing on the role of internal star scientists have suggested potential negative effects due to diseconomies when firms simultaneously rely on internal stars and collaborate with 'upstream' biotech firms (Hess & Rothermael, 2011), our findings suggest a different mechanism of diseconomies tied to internal stars, namely when they collaborate with external stars on translational research. We highlight that this substitution effect can be mitigated and positive collaboration premiums can be realized if there is a proper task division in the collaboration, with the internal star focusing on translation.

In closing, we note the most salient limitations of our study. First, our study focuses on large, R&D intensive pharmaceutical firms, and is not representative for smaller, specialized (biotechnology) firms for which ties to academic star scientists may be of a different nature due to the closeness of the biotech and university communities (Powell et al., 1996). Our findings for the pharmaceutical industry may neither be representative of basic research collaborations with star scientists in other science-based industries, such as ICT, drawing on scientific research in natural sciences. These industries are called 'complex', in the sense that firms tend to hold fragmented knowledge and need to cross-license to arrive at commercialization of products (Cohen et al., 2002; Czarnitzki et al., 2020). This contrasts with the 'discrete' nature of the pharmaceutical industry where a single patent can protect an entire commercial drug development trajectory. One can envisage that in complex industries exclusive access (dedication) to a star scientist may be less important, but this should be examined in future research.

Second, given the limited scope of our panel (1995–2002) our analysis does not allow the study of recent trends. While we cannot rule out that firms have changed their approach to collaborating with academic star scientists, the available evidence suggests that their reliance on excellence in basic research conducted at universities is still important, if not greater than during our observation window. The number of partnerships in biomedical sciences between corporate and academic or government institutions more than doubled from 12,672 in 2012 to 25,962 in 2016 according to the Nature Index (2019). Pharmaceutical firms have also taken many initiatives to further institutionalize these collaborations in order to more efficiently turn academic basic research into new drugs, such as Pfizer's *Global Centers for Therapeutic Innovation* or Merck & Co.'s structural partnership with the *California Institute for Biomedical Research* (Schuhmacher et al., 2016) to name just a few examples.[5] Whether these new collaboration initiatives have better succeeded in mitigating the concerns of dedication and translation revealed in our analysis is a question that we cannot answer with the available data and we leave it as a topic for follow-up research. Another evolution that has gained prominence after our observation period is the use of collaborative information technology in corporate innovation processes (Marion & Fixson, 2021). While digitization has undeniably affected the way people collaborate—also across the academia-industry boundary—it may be unlikely that it has fundamentally changed how companies establish partnerships with star scientists or the dedicated and/or translational nature of these collaborations. Yet also here, further research using more recent data could explore the role of digitization on the organization of collaboration between firms and star scientists.

Third, our analysis used a firm's citation-weighted patent count as dependent variable. A promising approach for future research would be to examine different performance measures that could specifically zoom in on radical invention with technological novelty as proposed in Verhoeven et al. (2016) and Strumsky and Lobo (2015). Alternatively, measures that are closer to innovation and commercialization performance would be of interest, although here the lags between research and performance can be rather long.

Fourth, although we used an elaborate specification that includes controls at the level of firms, stars and firm-star scientist collaborations to ensure that our findings are not confounded by selection bias, we cannot fully exclude the possibility of additional heterogeneity in projects and the related 'matching' between firms, star scientists, and collaborative contingencies. Our research methodology did not allow interpreting the results as causal relationships; finding a set of suitable instruments for not only the propensity to collaborate with star scientists but also the particular contingencies under which these collaborations takes place will remain a challenging task for future research. Fifth, our analysis focused on the individual and did not explicitly examine team effects: star scientists often manage laboratories and employ other scientists who may take up specific collaboration tasks. Given the difficulties in characterizing a very large group of individual non-star

[5]Our interviews did not signal major changes in the way that these collaborations work. Pharmaceutical firms are explicit about their continued ambition to team up with leading academic scientists: "*We know we can't do it all ourselves internally, and there is so much excellent research externally, especially within academia. For us, it's absolutely critical to work with the leading experts in their fields of research to drive the development of innovative therapeutics*." (Dr. Seeto, head of partnering and strategy at MedImmune of AstraZeneca, PharmaVOICE, 2014).

co-authors, our analysis did not examine potential comparable influences of collaboration types for basic research not involving star scientists.

Sixth, although controlling further for prior collaboration between internal and external stars did not show measurable effects, it is conceivable that the internal and external stars had prior personal and professional relationship before working in the research team of the firm. This may generate trust and psychological safety (e.g., Bruneel et al., 2010; Salas et al., 2018) and creates familiarity with each other's expertise and communication styles (Cattani et al., 2013; Reagans et al., 2005), allowing the team to function better. Studying such longitudinal individual scientists' informal interactions and their influence is an interesting topic for future research but will require the collection of individual survey data. Seventh, collaboration effectiveness may be facilitated by geographic proximity (Crescenzi et al., 2017; D'Este et al., 2013), but we were not able to measure the spatial context in our analysis. On the other hand, there is evidence that distance is less important compared to research quality in university-industry collaboration (Laursen et al., 2011) in particular for larger firms (Fantino et al., 2015) that benefit from clear advantages of scale and scope due their central research laboratories (Belderbos et al., forthcoming). Future research should aim to investigate the role of geographic proximity in firms' collaboration activity with academic stars.

Finally, our hypotheses and tests focused on heterogeneous conditions under which collaborations with star scientists can deliver benefits to collaborating firms, since the special status and capabilities of stars make collaboration under the right conditions essential. We acknowledge as a limitation that our analysis only examined the conditions pertaining to star collaboration compared with the average performance benefits of collaboration with non-stars. A challenging task of future research is to measure the same conditions for all individual non-star collaborative efforts of the firm in order to examine to what extent similar constraints and opportunities applies to these collaborations.

Our analysis focused on the two contingencies of dedication and translation since these were brought up in the interviews with practitioners involved as important, and because they both emanate from the core perceived differences between stars and other scientists: their higher opportunity costs and their extraordinary strengths in basic research. We acknowledge that other motivations for specific arrangements may play a role as well. For instance, we imagine that there can be dedicated star collaboration because the star wishes to limit collaboration with firms in the first place, or that arrangements do not include translation because the particular strength of stars is in basic research. Yet, these alternative explanations would rather predict negative associations between the contingencies and firm invention performance. Perhaps the lack of an overall positive relationship between a firm's engagement in star scientist collaboration and its invention performance is related to the presence of other, broader, collaboration objectives such as signaling research competence to potential new employees, hiring PhD students of star scientists, and general reputation building. Hence, even if specific types of star collaboration are negatively associated with direct invention success, longer term effects may compensate, and the motivation for star collaborations may lie elsewhere. Motivations for, and implications of, basic research collaboration arrangements and in particular dedication and translation will also be different if examined from the perspective of the academic star scientist. We hope that future research can provide more systematic insights into the variety of drivers of basic research collaborations, in particular from the perspective of the (star) scientists. The limitations of our study suggest a rich agenda for future research.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ETHICS STATEMENT

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

ORCID

Linde Colen https://orcid.org/0000-0002-0489-668X
René Belderbos https://orcid.org/0000-0002-4083-3387
Stijn Kelchtermans https://orcid.org/0000-0002-9977-1926
Bart Leten https://orcid.org/0000-0002-9140-1349

REFERENCES

Agrawal, Ajay. 2006. "Engaging the Inventor: Exploring Licensing Strategies for University Inventions and the Role of Latent Knowledge." *Strategic Management Journal 27*: 63–79.

Ahuja, Gautam. 2000. "Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study." *Administrative Science Quarterly 45*(3): 425–55.

Almeida, Paul, Jan Hohberger, and Pedro Parada. 2011. "Individual Scientific Collaborations and Firm-level innovation." *Industrial and Corporate Change 20*(6): 1571–99.

Arora, Ashish, Sharon Belenzon, and Andrea Patacconi. 2018. "The Decline of Science in Corporate R&D." *Strategic Management Journal 39*: 3–32.

Arora, Ashish, and Alfonso Gambardella. 1990. "Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology." *The Journal of Industrial Economics 38*(4): 361–79.

Arora, Ashish, and Alfonso Gambardella. 1994. "Evaluating Technological Information and Utilizing It: Scientific Knowledge, Technological Capability, and External Linkages in

Biotechnology." *Journal of Economic Behavior and Organization 24*(1): 91–114.

Arrow, Kenneth. 1962. "Economic Welfare and the Allocation of Resources for Invention." In *The Rate and Direction of Inventive Activity*, edited by Richard R. Nelson, 609–26. Princeton, NJ: Princeton University Press.

Arundel, Anthony, and Isabelle Kabla. 1998. "What Percentage of Innovations are Patented? Empirical Estimates for European Firms." *Research Policy 27*(2): 127–41.

Azoulay, Pierre, Toby Stuart, and Yanbo Wang. 2014. "Matthew: Effect or Fable?" *Management Science 60*(1): 92–109.

Baba, Yasunori, Naohiro Shiijo, and Silvia Sedita. 2009. "How Do Collaborations with Universtities Affect Firm's Innovation Performance? The Role of 'Pasteur Scientists' in the Advanced Materials Field." *Research Policy 38*: 756–64.

Banal-Estañol, Albert, Inés Macho-Stadler, and David Pérez-Castrillo. 2018. "Endogenous Matching in University-Industry Collaboration: Theory and Empirical Evidence from the United Kingdom." *Management Science 64*(4): 1591–608.

Belderbos, René, Martin Carree, and Boris Lokshin. 2004. "Cooperative R&D and Firm Performance." *Research Policy 33*(10): 1477–92.

Belderbos, René, Victor A. Gilsing, and Shinya Suzuki. 2016. "Direct and Mediated Ties to Universities: 'Scientific' Absorptive Capacity and Innovation Performance of Pharmaceutical Firms." *Strategic Organization 14*(1): 32–52.

Belderbos, René, Stijn Kelchtermans, and Bart Leten. forthcoming. "How Does Basic Research Improve Innovation Performance in the World's Major Pharmaceutical Firms?" *Industry & Innovation*.

Belderbos, René, Bart Leten, and Shinya Suzuki. 2017. "Scientific Research, Firm Heterogeneity, and Foreign R&D Locations of Multinational Firms." *Journal of Economics and Management Strategy 26*(3): 691–711.

Bercovitz, Janet, and Maryann Feldman. 2011. "The Mechanisms of Collaboration in Inventive Teams: Composition, Social Networks, and Geography." *Research Policy 40*: 81–93.

Blundell, Richard, Rachel Griffith, and John Van Reenen. 1995. "Dynamic Count Data Models of Technological Innovation." *The Economic Journal 105*(429): 333–44.

Bogers, Marcel, Ann-Kristin Zobel, Allan Afuah, Esteve Almirall, Sabine Brunswicker, Linus Dahlander, Lars Frederiksen, Annabelle Gawer, Marc Gruber, Stefan Haefliger, John Hagedoorn, Dennis Hilgers, Keld Laursen, Mats G. Magnusson, Ann Majchrzak, Ian P. McCarthy, Kathrin M. Moeslein, Satish Nambisan, Frank T. Piller, Agnieszka Radziwon, Cristina Rossi-Lamastra, Jonathan Sims, and Anne L. J. Ter Wal. 2017. "The Open Innovation Research Landscape: Established Perspectives and Emerging Themes Across Different Levels of Analysis." *Industry and Innovation 24*(1): 8–40.

Bruneel, Johan, Pablo D'Este, and Ammon Salter. 2010. "Investigating the Factors that Diminish the Barriers to University-Industry Collaboration." *Research Policy 39*: 858–68.

Cameron, Colin Adrian, and Pravin K. Trivedi. 2009. *Microeconometrics Using Stata*. College Station, TX: Stata Press.

Campbell, James J. 2005. *Understanding Pharma: A Primer on How Pharmaceutical Companies Really Work*. Raleigh: Pharmaceutical Institute.

Cassiman, Bruno, and Reinhilde Veugelers. 2006. "In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition." *Management Science 52*(1): 68–82.

Cassiman, Bruno, Reinhilde Veugelers, and Pluvia Zuniga. 2008. "In Search of Performance Effects of (In)direct Industry-Science Links." *Industrial and Corporate Change 17*(4): 611–46.

Cattani, Gino, Simone Ferriani, Marcello M. Mariani, and Stefano Mengoli. 2013. "Tackling the "Galacticos" Effect: Team Familiarity and the Performance of Star-studded Projects." *Industrial and Corporate Change 22*(6): 1629–62.

Chiou, Jing Yuan, Laura Magazzini, Fabio Pammolli, and Massimo Riccaboni. 2016. "Learning from Successes and Failures in Pharmaceutical R&D." *Journal of Evolutionary Economics 26*(2): 271–90.

Cloodt, Myriam, John Hagedoorn, and Hans Van Kranenburg. 2006. "Mergers and Acquisitions: Their Effect on the Innovative Performance of Companies in High-Tech Industries." *Research Policy 35*: 642–54.

Cockburn, Iain. 2007. "Is the Pharmaceutical Industry in a Productivity Crisis?" *Innovation Policy and the Economy 7*: 1–32.

Cockburn, Iain, and Rebecca Henderson. 1998. "Absorptive Capacity, Co-authoring Behaviour, and the Organization of Research in Drug Discovery." *The Journal of Industrial Economics 46*(2): 157–82.

Cohen, Wesley M., Akira Goto, Akiya Nagata, Richard R. Nelson, and John P. Walsh. 2002. "R&D Spillovers, Patents and the Incentives to Innovate in Japan and the United States." *Research Policy 31*(8–9): 1349–67.

Cohen, Wesley M., and Daniel A. Levinthal. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly 35*(1): 128–52.

Coleman, James. 1988. "Social Capital in the Creation of Human Capital." *The American Journal of Sociology 94*: 95–120.

Colyvas, Jeannette, Michael Crow, Annetine Gelijns, Roberto Mazzoleni, Richard R. Nelson, Nathan Rosenberg, and Bhaven N. Sampat. 2002. "How Do University Inventions Get into Practice?" *Management Science 48*(1): 61–72.

Crescenzi, Riccardo, Andrea Filippetti, and Simona Iammarino. 2017. "Academic Inventors: Collaboration and Proximity with Industry." *Journal of Technology Transfer 42*(4): 730–62.

Czarnitzki, Dirk, Katrin Hussinger, and Bart Leten. 2020. "How Valuable are Patent Blocking Strategies?" *Review of Industrial Organization 56*(3): 409–34.

D'Este, Pablo, Frederick Guy, and Simona Iammarino. 2013. "Shaping the Formation of University–Industry Research Collaborations: What Type of Proximity Does Really Matter?" *Journal of Economic Geography 13*(4): 537–58.

Dan, Li, Lorraine Eden, Michael A. Hitt, and R. Duane Ireland. 2008. "Friends, Acquaintances, or Strangers? Partner Selection in R&D Alliances." *The Academy of Management Journal 51*(2): 315–34.

Dasgupta, Partha, and Paul David. 1994. "Toward a New Economics of Science." *Research Policy 23*(5): 487–521.

Della Malva, Antonio, Stijn Kelchtermans, Bart Leten, and Reinhilde Veugelers. 2015. "Basic Science as a Prescription for Technological Breakthroughs in the Pharmaceutical Industry." *Journal of Technology Transfer 40*(4): 670–95.

Du, Jingshu, Bart Leten, and Wim Vanhaverbeke. 2014. "Managing Open Innovation Projects with Science-Based and Market-Based Partners." *Research Policy 43*(5): 828–40.

Elfenbein, Daniel, and Josh Lerner. 2012. "Exclusivity, Contingent Control Rights and the Design of Internet Portal Alliances." *Journal of Law, Economics, and Organization 28*(1): 45–76.

Fabrizio, Kira. 2009. "Absorptive Capacity and the Search for Innovation." *Research Policy 38*(2): 255–67.

Faems, Dries, Maddy Janssens, Anoop Madhok, and Bart Van Looy. 2008. "Toward an Integrative Perspective on Alliance Governance: Connecting Contract Design, Trust Dynamics, and Contract Application." *Academy of Management Journal 51*(6): 1053–78.

Fantino, Davide, Alessandra Mori, and Diego Scalise. 2015. "Collaboration Between Firms and Universities in Italy: the Role of a Firm's Proximity to Top-rated Departments." *Italian Economic Journal 1*(2): 219–51.

Fleming, Lee, and Olav Sorenson. 2004. "Science as a Map in Technological Search." *Strategic Management Journal 25*: 909–28.

Foray, Dominique, and Francesco Lissoni. 2010. "University Research and Public-private Interaction." In *Handbook of Economics of Innovation*, edited by Bronwyn H. Hall and Nathan Rosenberg, 275–314. Amsterdam: Elsevier.

Fuller, Anne, and Frank Rothaermel. 2012. "When Stars Shine: The Effect of Faculty Founders on New Technology Ventures." *Strategic Entrepreneurship Journal 6*: 220–35.

Gambardella, Alfonso. 1992. "Competitive Advantages from in-House Scientific Research: The U.S. Pharmaceutical Industry in the 1980s." *Research Policy 21*: 391–407.

Gambardella, Alfonso, Dietmar Harhoff, and Bart Verspagen. 2008. "The Value of European Patents." *European Management Review 5*(2): 69–84.

Gianiodis, Peter T., Gideon D. Markman, and Andreas Panagopoulos. 2016. "Entrepreneurial Universities and Overt Opportunism." *Small Business Economics 47*(3): 609–31.

Gittelman, Michelle, and Bruce Kogut. 2003. "Does Good Science Lead to Valiable Knowledge? Biotechnology Firms and the Evolutionary Logic of Citation Patterns." *Management Science 49*(4): 366–82.

Granovetter, Mark. 1983. "The Strength of Weak Ties: A Network Theory Revisited." *Sociological Theory 1*: 201–33.

Granovetter, Mark. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology 91*(3): 481–510.

Grigoriou, Konstantinos, and Frank T. Rothaermel. 2014. "Structural Microfoundations of Innovation: The Role of Relational Stars." *Journal of Management 40*(2): 586–615.

Groysberg, Boris, Linda-Eling Lee, and Ashish Nanda. 2008. "Can They Take It With Them? The Portability of Star Knowledge Workers' Performance." *Management Science 54*(7): 1213–30.

Groysberg, Boris, and Ashish. Nanda. 2004. "The Risky Business of Hiring Stars." *Harvard Business Review 82*(5): 92–101.

Groysberg, Boris, Jeffrey T. Polzer, and Hillary Anger Elfenbein. 2011. "Too Many Cooks Spoil the Broth: How High-Status Individuals Decrease Group Effectiveness." *Organization Science 22*(3): 722–37.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg. 2005. "Market Value and Patent Citations." *Rand Journal of Economics 36*(1): 16–38.

Hamilton, Kimberley. 2003. *Subfield and Level Classification of Journals*. CHI Report No. 2012-R CHI Research Inc.

Hess, Andrew M., and Frank T. Rothaermel. 2011. "When are Assets Complementary? Star Scientists, Strategic Alliances and Innovation in the Pharmaceutical Industry." *Strategic Management Journal 32*(8): 895–909.

Hess, Andrew M., and Frank T. Rothaermel. 2012. "Intellectual Capital and the Emergence of Biotechnology: Trends and Patterns: 1974–2006." *IEEE Transactions on Engineering Management 59*(1): 65–76.

Hicks, Diana M., Phoebe A. Isard, and Ben R. Martin. 1996. "A Morphology of Japanese and European Corporate Research Networks." *Research Policy 25*: 359–78.

Huckman, Robert S., Bradley R. Staats, and David M. Upton. 2009. "Team Familiarity, Role Experience and Performance: Evidence from Indian Software Service." *Management Science 55*(1): 85–100.

Jensen, Richard, and Marie C. Thursby. 2001. "Proofs and Prototypes for Sale: The Tale of University Licensing." *American Economic Review 91*(1): 240–59.

Kaiser, Ulrich, Hans C. Kongsted, Keld Laursen, and Ann-Kathrine Ejsing. 2018. "Experience Matters: The Role of Academic Scientist Mobility for Industrial Innovation." *Strategic Management Journal 39*(7): 1935–58.

Kaplan, Sarah, Fiona Murray, and Rebecca Henderson. 2003. "Discontinuities and Senior Management: Assessing the Role of Recognition in Pharmaceutical Firm Response to Biotechnology." *Industrial and Corporate Change 12*(4): 203–33.

Kehoe, Rebecca R., and Daniel Tzabbar. 2015. "Lighting the Way or Stealing the Shine? An Examination of the Duality in Star Scientists' Effects on Firm Innovation Performance." *Strategic Management Journal 36*: 709–27.

Kelchtermans, Stijn, and Reinhilde Veugelers. 2013. "Top Research Productivity and its Persistence: Gender as a Double-Edged Sword." *Review of Economics and Statistics 95*(1): 273–85.

Kola, Ismail, and John Landis. 2004. "Can the Pharmaceutical Industry Reduce Attrition Rates?" *Nature Reviews Drug Discovery 3*(8): 711–6.

Laursen, Keld, Toke Reichstein, and Ammon Salter. 2011. "Exploring the Effect of Geographical Proximity and University Quality on University–Industry Collaboration in the United Kingdom." *Regional Studies 45*(4): 507–23.

Leten, Bart, Rene Belderbos, and Bart Van Looy. 2007. "Technological Diversification, Coherence, and Performance of Firms." *Journal of Product Innovation Management 24*(6): 567–79.

Lotka, Alfred. 1926. "The Frequency Distribution of Scientific Productivity." *Journal of the Washington Academy of Science 16*(12): 317–24.

Luo, Xiaowei Rose, Kenneth W. Koput, and Walter W. Powell. 2009. "Intellectual Capital or Signal? The Effects of Scientists on Alliance Formation in Knowledge-Intensive Industries." *Research Policy 38*(8): 1313–25

Mansfield, Edwin. 1995. "Academic Research Underlying Industrial Innovations: Sources, Characteristics, and Financing." *The Review of Economics and Statistics 77*(1): 55–65.

Mansfield, Edwin. 1998. "Academic Research and Industrial Innovation: An Update of Empirical Findings." *Research Policy 26*: 773–6.

Marion, Tucker J., and Sebastian K. Fixson. 2021. "The Transformation of the Innovation Process: How Digital Tools are Changing Work, Collaboration, and Organizations in New Product Development." *Journal of Product Innovation Management 38*(1): 192–215.

Martínez, Catalina. 2011. "Patent Families: When Do Different Definitions Really Matter?" *Scientometrics 86*(1): 39–63.

Melin, Göran, and Olle Persson. 1996. "Studying Research Collaboration Using Co-authorships." *Scientometrics 36*(3): 363–77.

Melnychuk, Tetyana, Carsten Schultz, and Alexander Wirsich. 2021. "The Effects of University–Industry Collaboration in Preclinical Research on Pharmaceutical Firms' R&D Performance: Absorptive Capacity's Role." *Journal of Product Innovation Management 38*: 355–78.

Milne, Christopher-Paul, and Ashley Malins. 2012. *Academic-Industry Partnerships for Biopharmaceutical Research & Development: Advancing Medical Science in the U.S. Tufts Center for the Study of Drug Development*. Boston, MA: Tufts University School of Medicine.

Mindruta, Denisa. 2013. "Value Creation in University-Firm Research Collaborations: A Matching Approach." *Strategic Management Journal 34*: 644–65.

Mowery, David C., Joanne E. Oxley, and Brian S. Silverman. 1996. "Strategic Alliances and Interfirm Knowledge Transfers." *Strategic Management Journal 17*: 77–91.

Murray, Fiona. 2004. "The Role of Academic Inventors in Entrepreneurial Firms: Sharing the Laboratory Life." *Research Policy 33*(4): 643–59.

Narin, Francis, Kimberly S. Hamilton, and Dominic Olivastro. 1997. "The Increasing Linkage Between U.S. Technology and Public Science." *Research Policy 26*: 317–30.

Nature Index. *Top 5 Corporate–Academic Collaborations in Biomedical Sciences*. August 6, 2019. https://www.natureindex.com/news-blog/top-corporate-academic-collaborations-biomedical-sciences2019.

Nelson, Richard R. 1959. "The Simple Economics of Basic Scientific Research." *The Journal of Political Economy 67*(3): 297–306.

Oncurious. 2015. *Oncurious NV Appoints Prof Dr Peter Carmeliet as its Chief Scientific Strategy Advisor*. http://www.oncurious.com/sites/default/files/upload/news/Oncurious_ENG_Press%20release_Carmeliet_FINAL.pdf.

Owen-Smith, Jason, and Walter W. Powell 2004. "Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community." *Organization Science 15*(1): 5–21.

Perkmann, Markus, Valentina Tartari, Maureen McKelvey, Erkko Autio, Anders Broström, Pablo D'Este, Riccardo Fini, Aldo Geuna, Rosa Grimaldi, Alan Hughes, Stefan Krabel, Michael Kitson, Patrick Llerena, Franceso Lissoni, Ammon Salter, and Maurizio Sobrero. 2013. "Academic Engagement and Commercialisation: A Review of the Literature on University–Industry Relations." *Research Policy 42*(2): 423–42.

PharmaVOICE. 2014. *New Models for Academic Partnerships. Contributed by Denise Mushko*. January 17, 2020. https://www.pharmavoice.com/article/academic-partnerships/.

Plewa, Carolin, Nisha Korff, Thomas Baaken, and Greg Macpherson. 2013. "Universty-Industry Linkage Evolution: An Empirical Investigation of Relational Success Factors." *R&D Management 43*(4): 365–80.

Powell, Walter W., Kenneth W. Koput, and Laurel Smith-Doerr. 1996. "Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology." *Administrative Science Quarterly 41*(1): 116–45.

Prato, Matteo, and Fabrizio Ferraro. 2018. "Starstruck: How Hiring High-Status Employees Affects Incumbents' Performance." *Organization Science 29*(5): 755–74.

Rafols, Ismael, Michael M. Hopkins, Jarno Hoekman, Josh Siepel, Alice O'Hare, Antonio Perianes-Rodríguez, and Paul Nightingale. 2014. "Big Pharma, Little Science? A Bibliometric Perspective on Big Pharma's R&D Decline." *Technological Forecasting and Social Change 81*: 22–38.

Reagans, Ray, Linda Argote, and Daria Brooks. 2005. "Individual Experience and Experience Working Together: Predicting Learning Rates from Knowing Who Knows What and Knowing How to Work Together." *Management Science 51*(6): 869–81.

Rosen, Sherwin. 1981. "The Economics of Superstars." *The American Economic Review 71*(5): 845–58.

Rosenberg, Nathan. 1990. "Why Do Firms Do Basic Research (with their Own Money)?" *Research Policy 19*(2): 165–74.

Rothaermel, Frank T., and Andrew M. Hess. 2007. "Building Dynamic Capabilities: Innovation Driven by Individual-, Firm-, and Network-Level Effects." *Organization Science 18*(6): 898–921.

Salas, Eduardo, Denise L. Reyes, and Susan H. McDaniel. 2018. "The Science of Teamwork: Progress, Reflections and the Road Ahead." *American Psychologist 73*(4): 593–600.

Sauermann, Henry, and Michael Roach. 2012. "Taste for Science, Taste for Commercialization, and Hybrid Scientists." Paper presented at 34th DRUID Conference, June 19–21.

Sauermann, Henry, and Michael Roach. 2014. "Not All Scientists Pay to be Scientists: Heterogeneous Preferences for Publishing in Industrial Research." *Research Policy 43*(1): 32–47.

Sauermann, Henry, and Paula Stephan. 2013. "Conflicting Logics? A Multidimensional View of Industrial and Academic Science." *Organization Science 24*(3): 889–909.

Schuhmacher, Alexander, Oliver Gassmann, and Markus Hinder. 2016. "Changing R&D Models in Research-Based Pharmaceutical Companies." *Journal of Translational Medicine 14*(1): 105.

Soh, Pek-Hooi, and Annapoornima M. Subramanian. 2014. "When Do Firms Benefit from University-Industry R&D Collaborations? The Implications of Firm R&D Focus on Scientific Research and Technological Recombination." *Journal of Business Venturing 29*(6): 807–21.

Sorenson, Olav, Jan W. Rivkin, and Lee Fleming. 2006. "Complexity, Networks and Knowledge Flow." *Research Policy 35*: 994–1017.

Stephan, Paula E., and David B. Audretsch. 1996. "Company-Scientist Locational Links: The Case of Biotechnology." *American Economic Review 86*(3): 641–52.

Stern, Scott. 2004. "Do Scientists Pay to Be Scientists?" *Management Science 50*(6): 835–53.

Stokes, Donald E. 1997. *Pasteur's Quadrant. Basic Science and Technological Innovation*. Washington, DC: Bookings Institution Press.

Strumsky, Deborah, and José Lobo. 2015. "Identifying the Sources of Technological Novelty in the Process of Invention." *Research Policy 44*: 1445–61.

Subramanian, Annapoornima M., Kwanghui Lim, and Pek-Hooi Soh. 2013. "When Birds of a Feather Don't Flock Together: Different Scientists and the Roles they Play in Biotech R&D Alliances." *Research Policy 42*(3): 1–18.

Tartari, Valentina, Ammon Salter, and Pablo D'Este. 2012. "Crossing the Rubicon: Exploring the Factors that Shape Academics' Perceptions of the Barriers to Working with Industry." *Cambridge Journal of Economics 36*(3): 655–77.

Thursby, Jerry G., and Marie C. Thursby. 2011. "Has the Bayh-Dole Act Compromised Basic Research?" *Research Policy 40*(8): 1077–83.

Torvik, Vetle I., and Neil R. Smalheiser. 2009. "Author Name Disambiguation in MEDLINE." *ACM Transactions on Knowledge Discovery from Data 3*(3): 1–29.

Torvik, Vetle I., Marc Weeber, Don R. Swanson, and Neil R. Smalheiser. 2005. "A Probabilistic Similarity Metric for Medline Records: A Model for Author Name Disambiguation." *JASIST 56*(2): 140–58.

Trajtenberg, Manuel. 1990. "A Penny for Your Quotes: Patent Citation and the Value of Innovations." *Rand Journal of Economics 21*: 172–87.

Tzabbar, Daniel, and Rebecca R. Kehoe. 2013. "Can Opportunity Emerge From Disarray? An Examination of Exploration and Exploitation Following Star Scientist Turnover." *Journal of Management 40*(2): 449–82.

Verhoeven, Dennis, Jurriën Bakker, and Reinhilde Veugelers. 2016. "Measuring Technological Novelty with Patent-Based Indicators." *Research Policy 45*(3): 707–23.

Woolf, Steven H. 2008. "The Meaning of Translational Research and Why it Matters." *JAMA 299*(2): 211–3.

Woolston, Chris. 2016. "Group Dynamics: A Lab of their Own." *Nature 531*(7593): 263–5.

Zucker, Lynne G., Michael R. Darby, and Marilynn B. Brewer. 1998. "Intellectual Human Capital and the Birth of US Biotechnology Enterprises." *American Economic Review 88*(1): 290–306.

Zucker, Lynne G., Michael R. Darby, and Jeff S. Armstrong. 2002. "Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology." *Management Science 48*(1): 138–53.

AUTHOR BIOGRAPHIES

Dr. Linde Colen is a post-doctoral researcher at Hasselt University. Her research interest are knowledge transfer across and within organizations, university-industry collaboration and economics of science.

Dr. René Belderbos is full professor of strategy at the KU Leuven and part-time professor of International Corporate Strategy at Maastricht University and UNU-MERIT (The Netherlands). His research focuses on the innovation and international business strategies of multinational firms.

Dr. Stijn Kelchtermans is an associate professor of innovation and strategy at the KU Leuven and Hasselt University. His areas of research include the economics of science and innovation, industry-science links and markets for technology.

Dr. Bart Leten is professor of technology and innovation management at the KU Leuven and Hasselt University. His research focuses on innovation, international business, human capital and intellectual property strategies of multinational firms.

How to cite this article: Colen, Linde, René Belderbos, Stijn Kelchtermans, and Bart Leten. 2021. "Reaching for the Stars: When Does Basic Research Collaboration Between Firms and Academic Star Scientists Benefit Firm Invention Performance?" *Journal of Product Innovation Management* 00: 1–43. https://doi.org/10.1111/jpim.12607.

APPENDIX

This appendix reports details on a number of robustness tests and alternative specifications. The final table lists the firms included in the sample.

Heterogeneity in collaboration experience across types of collaboration projects

We examined whether there is heterogeneity in the influence of past collaboration experience depending on the type of collaboration. While our main models control for the average collaboration experience of the firm and academic stars, we also explore a model expansion in which we include eight variables that capture the collaboration experience for each type of star scientist collaboration.

Table A1 reports the empirical results if eight collaborative experience variables are included, one for each academic star collaboration type. The results show no contingency-specific collaborative experience effects at conventional significance (5%) levels. The focal results and tests for the hypotheses are not affected, but we do note that the test statistic for a performance premium of translational collaboration without internal star involvement becomes insignificant, which likely reflects a lesser ability to estimate coefficients with precision.

Partner matching

The emerging literature on matching in research collaboration has suggested that particular matches between the

TABLE A1 Academic star collaboration in basic research and firms' innovation performance: Collaborative research experience heterogeneity

		Coef.	*z*-value (*p*-value)
Key variables			
Log (R&D)		0.15	2.15
			(0.032)
Basic research publications/R&D		0.01	0.11
			(0.916)
Basic research co-publications with academia/Basic research publications		0.72	2.07
			(0.039)
Share of basic research co-publications with academia			
… without internal star and without academic stars		Reference group	
… without internal stars and with academic stars			
… which are dedicated and translational	β_{1a}	1.92	3.18
			(0.002)
… which are dedicated and non-translational	β_{1b}	1.46	1.64
			(0.100)
… which are non-dedicated and translational	β_{1c}	0.06	0.06
			(0.949)
… which are non-dedicated and non-translational	β_{1d}	−1.85	−2.71
			(0.007)
…with internal stars and with academic stars			
… which are dedicated and translational	β_{2a}	−5.52	−1.46
			(0.145)
… which are dedicated and non-translational	β_{2b}	9.63	3.18
			(0.002)
… which are non-dedicated and translational	β_{2c}	−9.47	−3.24
			(0.001)
… which are non-dedicated and non-translational	β_{2d}	−3.94	−3.09
			(0.002)
…with internal stars and without academic stars		−0.21	−0.32
			(0.746)

(Continues)

TABLE A1 (Continued)

	Coef.	*z*-value (*p*-value)
Firm controls		
Technological diversity	−0.01	−0.13 (0.898)
Technological diversity^2	0.00	−0.48 (0.629)
Research alliances/R&D	0.25	0.55 (0.583)
Presence of internal star)	0.10	0.89 (0.376)
Log (firm age)	0.36	3.19 (0.001)
Firm research quality	−0.01	−2.28 (0.022)
Firm research diversity	2.76	0.87 (0.383)
Star controls		
Research quality of academic stars	0.00	−1.77 (0.077)
Research diversity of academic stars	0.55	1.34 (0.180)
Star-firm collaboration controls		
Quality of basic collaborations with academic stars	0.16	2.73 (0.006)
experience co-publications between firm and academic stars of ...		
... collaborations without internal stars, with dedicated and translational academic stars	0.02	1.88 (0.061)
... collaborations without internal stars, with dedicated and non-translational academic stars	0.07	1.04 (0.298)
... collaborations without internal stars, with non-dedicated and translational academic stars	0.04	1.88 (0.060)
... collaborations without internal stars, with non-dedicated and non-translational academic stars	−0.03	−0.66 (0.511)
... collaborations with internal stars, with dedicated and translational academic stars	−0.01	−1.17 (0.242)
... collaborations with internal stars, with dedicated and non-translational academic stars	−0.02	−0.90 (0.370)
... collaborations with internal stars, with non-dedicated and translational academic stars	−0.02	−1.41 (0.159)
... collaborations with internal stars, with non-dedicated and non-translational academic stars	0.02	0.73 (0.465)
Pseudo firm-fixed effects and year dummies		
Pseudo-fixed effects	0.57	11.60 (0.000)

TABLE A1 (Continued)

	Coef.		z-value (p-value)
Year dummies	Yes		
Constant	1.71		3.62
			(0.000)
Log likelihood	−25,963.03		
Hypotheses tests			
	χ^2	(Prob > χ^2)	Answer
H1	14.84	(0.000)	Yes
H2 all collaborations	9.66	(0.002)	No (reduced benefit)
Collaborations without internal stars	3.07	(0.080)	No
H3	14.04	(0.000)	Yes

Notes: All models have 406 observations. p-value of robust standard errors in parentheses.

capabilities of a firm and its academic partner may be more productive (Banal-Estanol, 2018; Mindruta, 2013). These studies focused on the entire spectrum of firms and academics rather than on the very top of the distribution (star scientists). Nevertheless, it is worthwhile investigating whether the suggested performance-enhancing influences are observed in the context of our study. Based on these prior studies, we augment the model with measures of positive assortative matching on research quality and basic research orientation (Banal-Estañol et al., 2018) and negative assortative matching on research diversity (Mindruta, 2013). The matching variables are constructed by assessing, for each star-firm collaboration, how the star (and firm) scores relative to the mean for all stars (firms) on these dimensions. If a star and firm score similarly (i.e., both are above or below the mean) on a dimension, the star-firm collaboration is classified as positive assortative matching for this dimension, and vice versa for negative assortative matching. The matching variables measure the share of star collaborations for which there is positive assortative matching (research quality and basic research orientation) and negative assortative matching (research diversity) between the firm and the star.

The results are shown in Table A2. The empirical results do not suggest a further influence of matching, while the focal results and hypothesis tests remain unchanged. This is likely to be related to our focused and selective context of star scientist collaboration in the pharmaceutical industry and the fact that the analysis already controls for collaboration quality and experience.

Heterogeneity in the scientific quality of types of collaboration projects

We examine more in detail whether the choice for certain types of academic star scientist collaborations may be associated with the underlying quality of the proposed research collaborations. While our main models control for the average quality of collaborative basic research with academic star scientists, we also explore an expansion of the model in which we include eight variables that capture the quality of the projects for each type of star scientist collaboration, measured by the forward citations to the associated co-authored papers.

Table A3 shows that variation in collaboration type-specific research quality explains some residual variation in innovation benefits for non-dedicated collaborations involving internal stars, while there appears to be a negative association between research quality and innovation for non-dedicated non-translation collaboration without internal star involvement. The focal results of our analysis do not change, with Hypotheses 1 and 3 supported, while support for Hypothesis 2, as before, is confined to collaborations without internal star involvement.

Heterogeneity in opportunities across research domains

The presence of star scientists might be concentrated in particular fields, arguably those fields with greater research opportunities. As similarly firms' might be more active in fields with greater research opportunities, the analysis shown in Table A4 controls for the (average) research opportunities in the domains in which the focal firm collaborates with stars. Opportunities are measured by the worldwide growth in publications in the 44 scientific domains that we also use to identify stars. Adding this variable did not produce significant results, while the core results remained unchanged.

Collaborative network of academic stars

Beside human capital, social capital is regarded an important asset of star scientists. While the included controls

TABLE A2 Academic star collaboration in basic research and firms' innovation performance: Firm-star matching

		Model 1		Model 2		Model 3	
		Coef.	*z*-value (*p*-value)	Coef.	*z*-value (*p*-value)	Coef.	*z*-value (*p*-value)
Key variables							
Log (R&D)		0.23	3.70 (0.000)	0.24	3.86 (0.000)	0.18	2.99 (0.003)
Basic research publications/R&D		0.03	0.62 (0.532)	0.03	0.72 (0.472)	0.01	0.27 (0.787)
Basic research co-publications with academia/Basic research publications		1.04	3.10 (0.002)	1.04	3.13 (0.002)	0.82	2.46 (0.014)
Share of basic research co-publications with academia							
... without internal star and without academic stars		Reference group					
... with academic stars				−0.44	−1.08 (0.278)		
... *without internal stars and with academic stars*							
... which are dedicated and translational	β_{1a}					2.26	3.74 (0.000)
... which are dedicated and non-translational	β_{1b}					1.94	2.09 (0.037)
... which are non-dedicated and translational	β_{1c}					0.46	0.44 (0.663)
... which are non-dedicated and non-translational	β_{1d}					−2.15	−3.14 (0.002)
... *with internal stars and with academic stars*							
... which are dedicated and translational	β_{2a}					−6.09	−1.83 (0.067)
... which are dedicated and non-translational	β_{2b}					7.31	2.39 (0.017)
... which are non-dedicated and translational	β_{2c}					−10.30	−4.36 (0.000)
... which are non-dedicated and non-translational	β_{2d}					−4.41	−4.11 (0.000)
... with internal stars and without academic stars						0.09	0.14 (0.890)
Firm controls							
Technological diversity		−0.02	−0.19 (0.850)	−0.02	−0.21 (0.831)	0.00	0.01 (0.994)
Technological diversity^2		0.00	−0.41 (0.684)	0.00	−0.39 (0.699)	0.00	−0.63 (0.529)
Research alliances/R&D		0.40	0.62 (0.538)	0.41	0.61 (0.543)	0.11	0.23 (0.816)
Presence of internal star		0.04	0.36 (0.717)	0.08	0.68 (0.495)	0.13	1.10 (0.272)

TABLE A2 (Continued)

	Model 1		Model 2		Model 3	
	Coef.	*z*-value (*p*-value)	Coef.	*z*-value (*p*-value)	Coef.	*z*-value (*p*-value)
Log (firm age)	0.18	1.64 (0.101)	0.17	1.60 (0.109)	0.34	3.39 (0.001)
Firm research quality	−0.01	−2.16 (0.031)	−0.01	−2.16 (0.030)	0.00	−1.82 (0.069)
Firm research diversity	2.66	0.77 (0.442)	2.70	0.78 (0.438)	1.89	0.56 (0.573)
Star controls						
Research quality of academic stars	−0.01	−4.76 (0.000)	−0.01	−4.43 (0.000)	0.00	−2.13 (0.033)
Research diversity of academic stars	1.91	2.40 (0.016)	1.88	2.37 (0.018)	1.71	2.34 (0.019)
Star-firm collaboration controls						
Quality of basic collaborations with academic stars	0.21	3.04 (0.002)	0.21	3.01 (0.003)	0.21	3.06 (0.002)
Experience between firm and academic stars	0.01	1.72 (0.086)	0.02	2.16 (0.030)	0.05	3.66 (0.000)
Star-firm matching controls						
Share of basic coll. with academic stars						
… positive assortative matching on research quality	−0.84	−2.01 (0.045)	−0.84	−2.04 (0.041)	−0.40	−1.03 (0.305)
… positive assortative matching on basic research focus	−0.96	−0.97 (0.331)	−0.90	−0.91 (0.363)	0.52	0.54 (0.589)
… negative assortative matching on research diversity	0.95	0.80 (0.423)	1.01	0.85 (0.397)	−1.39	−1.19 (0.234)
Pseudo firm-fixed effects and year dummies						
Pseudo firm-fixed effects	0.59	10.86 (0.000)	0.58	10.88 (0.000)	0.54	10.36 (0.000)
Year dummies	Yes		Yes		Yes	
Constant	1.90	3.87 (0.000)	1.90	3.86 (0.000)	1.70	3.53 (0.000)
Log likelihood	−31,725.63		−30,790.44		−26,476.61	
Hypotheses tests						
	χ^2		(Prob > χ^2)		Answer	
H1	16.75		(0.000)		Yes	
H2 all collaborations	10.20		(0.001)		No (reduced benefit)	
Collaborations without internal stars	4.35		(0.037)		Yes	
H3	14.56		(0.000)		Yes	

Notes: All models have 406 observations. *p*-value of robust standard errors in parentheses.

for the stars' publication, citation, and domain diversity already captures this heterogeneity among stars, we added a measure of the collaborative network size of academic stars to our model in Table A5. The collaborative network size is measured as the average of the total number of co-authors of the academic stars in the Authority data

TABLE A3 Academic star collaboration in basic research and firms' innovation performance: Collaborative research quality heterogeneity

		Coef.	*z*-value (*p*-value)
Key variables			
Log (R&D)		0.20	3.29 (0.001)
Basic research publications/R&D		0.02	0.31 (0.755)
Basic research co-publications with academia/Basic research publications		0.78	2.30 (0.021)
Share of basic research co-publications with academia			
... without internal star and without academic stars		Reference group	
... without internal stars and with academic stars			
... which are dedicated and translational	β_{1a}	2.16	3.63 (0.000)
... which are dedicated and non-translational	β_{1b}	1.22	1.44 (0.151)
... which are non-dedicated and translational	β_{1c}	0.42	0.42 (0.676)
... which are non-dedicated and non-translational	β_{1d}	−2.13	−3.02 (0.003)
...with internal stars and with academic stars			
... which are dedicated and translational	β_{2a}	−5.01	−1.16 (0.248)
... which are dedicated and non-translational	β_{2b}	7.95	2.55 (0.011)
... which are non-dedicated and translational	β_{2c}	−9.68	−4.35 (0.000)
... which are non-dedicated and non-translational	β_{2d}	−4.48	−3.96 (0.000)
...with internal stars and without academic stars		−0.02	−0.03 (0.980)
Firm controls			
Technological diversity		0.01	0.05 (0.957)
Technological diversity^2		0.00	−0.63 (0.531)
Research alliances/R&D		0.28	0.60 (0.548)
Presence of internal star		0.08	0.70 (0.484)
Log (firm age)		0.32	3.06 (0.002)
Firm research quality		−0.01	−2.22 (0.026)
Firm research diversity		2.69	0.81 (0.419)

TABLE A3 (Continued)

	Coef.		z-value (p-value)
Star controls			
Research quality of academic stars	0.00		−1.01 (0.311)
Research diversity of academic stars	0.55		1.32 (0.187)
Star-firm collaboration controls			
Experience between firm and academic stars	0.04		3.29 (0.001)
Quality of			
... collaborations without internal stars, with dedicated and translational academic stars	0.00		−0.06 (0.948)
... collaborations without internal stars, with dedicated and non-translational academic stars	0.02		0.43 (0.667)
... collaborations without internal stars, with non-dedicated and translational academic stars	0.01		0.72 (0.470)
... collaborations without internal stars, with non-dedicated and non-translational academic stars	0.00		0.05 (0.958)
... collaborations with internal stars, with dedicated and translational academic stars	−0.14		−1.59 (0.111)
... collaborations with internal stars, with dedicated and non-translational academic stars	0.05		0.98 (0.325)
... collaborations with internal stars, with non-dedicated and translational academic stars	0.05		1.11 (0.266)
... collaborations with internal stars, with non-dedicated and non-translational academic stars	0.08		1.49 (0.136)
Pseudo firm fixed effects and year dummies			
Pseudo firm fixed effects	0.55		10.48 (0.000)
Year dummies	Yes		
Constant	1.68		3.43 (0.001)
Log likelihood	−26,854.04		
Hypotheses tests			
	χ^2	(Prob > χ^2)	Answer
H1	13.45	(0.000)	Yes
H2 all collaborations	7.11	(0.008)	No (reduced benefit)
Collaborations without internal stars	7.11	(0.008)	Yes
H3	12.68	(0.000)	Yes

Notes: All models have 406 observations. p-value of robust standard errors in parentheses.

TABLE A4 Academic star collaboration in basic research and firms' inventive performance: Controlling for research opportunities in the research domains of collaborations with academic stars

		Coef.	z-value (p-value)
Key variables			
Log (R&D)		0.19	3.12 (0.002)
Basic research publications/R&D		0.03	0.52 (0.600)
Basic research co-publications with academia/Basic research publications		0.83	2.44 (0.015)
Share of basic research co-publications with academia			
… without internal star and without academic stars		Reference group	
… without internal stars and with academic stars			
… which are dedicated and translational	β_{1a}	2.13	3.59 (0.000)
… which are dedicated and non-translational	β_{1b}	1.29	1.50 (0.134)
… which are non-dedicated and translational	β_{1c}	0.47	0.44 (0.659)
… which are non-dedicated and non-translational	β_{1d}	−2.17	−3.18 (0.001)
… with internal stars and with academic stars			
… which are dedicated and translational	β_{2a}	−6.19	−1.71 (0.087)
… which are dedicated and non-translational	β_{2b}	8.13	2.60 (0.009)
… which are non-dedicated and translational	β_{2c}	−10.27	−4.13 (0.000)
… which are non-dedicated and non-translational	β_{2d}	−4.46	−4.02 (0.000)
…with internal stars and without academic stars		−0.12	−0.17 (0.865)
Firm controls			
Technological diversity		0.00	0.01 (0.993)
Technological diversity^2		0.00	−0.61 (0.543)
Research alliances/R&D		0.23	0.52 (0.603)
Dummy (presence of internal star)		0.13	1.13 (0.257)
Log (firm age)		0.34	3.30 (0.001)
Firm research quality		−0.01	−2.33 (0.020)

TABLE A4 (Continued)

	Coef.		z-value (p-value)
Firm research diversity	2.92		0.87 (0.383)
Stars controls			
Research quality of academic stars	0.00		−1.30 (0.193)
Research diversity of academic stars	0.52		1.19 (0.236)
Star-firm collaboration controls			
Experience between firm and academic stars	0.17		2.62 (0.009)
Quality of basic collaborations with academic stars	0.05		3.48 (0.001)
Research opportunities in domains of collaboration with academic stars	0.00		0.25 (0.800)
Pseudo firm-fixed effects and year dummies			
Pseudo-fixed effects	0.54		10.59 (0.000)
Year dummies	Yes		
Constant	1.68		3.43 (0.001)
Log likelihood	−26,993.08		
Hypotheses tests			
	χ^2	(Prob > χ^2)	Answer
H1	15.04	(0.000)	Yes
H2 all collaborations	9.61	(0.002)	No (reduced benefit)
Collaborations without internal stars	6.15	(0.013)	Yes
H3	15.33	(0.000)	Yes

Notes: All models have 406 observations. p-value of robust standard errors in parentheses.

set (Torvik et al., 2005; Torvik & Smalheiser, 2009). No significant effect was found for the collaborative network size of stars, and core results were unaffected.

Extension of the patent citation window

We examined whether the results are sensitive to the choice of the citation window for the innovation performance measure. Employing an extended eight-year citation window, we observed no substantive differences in the empirical results, as shown in Table A6.

Results when omitting 3 firms without star collaboration

We estimated the model once more with 3 firms for which no collaboration with academic stars was observed during the window of analysis omitted. All three of these omitted firms had five or more years without a basic research publication. The second column of Table A7 contains the estimation results, which show similar results as the main model. The final rows of this Table also confirm that all findings are robust for this alternative sample.

TABLE A5 Academic star collaboration in basic research and firms' inventive performance: Controlling for the star scientists' collaborative network

		Coef.	*z*-value (*p*-value)
Key variables			
Log (R&D)		0.18	3.07
			(0.002)
Basic research publications/R&D		0.02	0.46
			(0.648)
Basic research co-publications with academia/Basic research publications		0.85	2.48
			(0.013)
Share of basic research co-publications with academia			
... without internal star and without academic stars		Reference group	
... *without internal stars and with academic stars*			
... which are dedicated and translational	β_{1a}	2.17	3.58
			(0.000)
... which are dedicated and non-translational	β_{1b}	1.29	1.48
			(0.139)
... which are non-dedicated and translational	β_{1c}	0.43	0.41
			(0.685)
... which are non-dedicated and non-translational	β_{1d}	−2.14	−3.11
			(0.002)
... *with internal stars and with academic stars*			
... which are dedicated and translational	β_{2a}	−6.32	−1.73
			(0.083)
... which are dedicated and non-translational	β_{2b}	8.13	2.61
			(0.009)
... which are non-dedicated and translational	β_{2c}	−10.28	−4.12
			(0.000)
... which are non-dedicated and non-translational	β_{2d}	−4.50	−4.02
			(0.000)
...with internal stars and without academic stars		−0.06	−0.09
			(0.928)
Firm controls			
Technological diversity		0.00	0.01
			(0.996)
Technological diversity^2		0.00	−0.61
			(0.544)
Research alliances/R&D		0.25	0.56
			(0.573)
Dummy (presence of internal star)		0.12	1.04
			(0.299)
Log (firm age)		0.35	3.32
			(0.001)
Firm research quality		−0.01	−2.35
			(0.019)

TABLE A5 (Continued)

	Coef.		z-value (p-value)
Firm research diversity	2.92		0.88 (0.379)
Stars controls			
Research quality of academic stars	0.00		−1.48 (0.139)
Research diversity of academic stars	0.59		1.39 (0.165)
Collaborative network of academic stars	0.00		−0.67 (0.504)
Star-firm collaboration controls			
Experience between firm and academic stars	0.17		2.9 (0.004)
Quality of basic collaborations with academic stars	0.05		3.53 (0.000)
Pseudo firm fixed effects and year dummies			
Pseudo fixed effects	0.54		10.54 (0.000)
Year dummies	Yes		
Constant	1.69		3.45 (0.001)
Log likelihood	−26,981.26		
Hypotheses tests			
	χ^2	(Prob > χ^2)	Answer
H1	14.84	(0.000)	Yes
H2 all collaborations	9.76	(0.002)	No (reduced benefit)
Collaborations without internal stars	6.17	(0.013)	Yes
H3	15.49	(0.000)	Yes

Notes: All models have 406 observations. p-value of robust standard errors in parentheses.

TABLE A6 Academic star collaboration in basic research and firms' innovation performance: 8-year citation window for the dependent variable

		Coef.	*z*-value (*p*-value)
Key variables			
Log (R&D)		0.13	2.17
			(0.030)
Basic research publications/R&D		0.02	0.45
			(0.651)
Basic research co-publications with academia/Basic research publications		0.59	1.75
			(0.081)
Share of basic research co-publications with academia			
... without internal star and without academic stars		Reference group	
... without internal stars and with academic stars			
... which are dedicated and translational	β_{1a}	2.36	3.51
			(0.000)
... which are dedicated and non-translational	β_{1b}	1.35	1.45
			(0.147)
... which are non-dedicated and translational	β_{1c}	0.45	0.45
			(0.654)
... which are non-dedicated and non-translational	β_{1d}	−2.30	−3.13
			(0.002)
... with internal stars and with academic stars			
... which are dedicated and translational	β_{2a}	−4.57	−1.34
			(0.179)
... which are dedicated and non-translational	β_{2b}	7.58	2.39
			(0.017)
... which are non-dedicated and translational	β_{2c}	−9.56	−3.89
			(0.000)
... which are non-dedicated and non-translational	β_{2d}	−3.94	−3.60
			(0.0037)
...with internal stars and without academic stars		−0.67	−0.95
			(0.344)
Firm controls			
Technological diversity		−0.03	−0.28
			(0.779)
Technological diversity^2		0.00	−0.31
			(0.756)
Research alliances/R&D		−0.01	−0.02
			(0.987)
Dummy (presence of internal star)		0.15	1.28
			(0.201)
Log (firm age)		0.36	3.34
			(0.001)
Firm research quality		−0.01	−2.27
			(0.023)

TABLE A6 (Continued)

	Coef.		z-value (p-value)
Firm research diversity	2.71		0.90 (0.366)
Stars controls			
Research quality of academic stars	0.00		−1.48 (0.140)
Research diversity of academic stars	0.55		1.41 (0.159)
Star-firm collaboration controls			
Experience between firm and academic stars	0.16		2.64 (0.008)
Quality of basic collaborations with academic stars	0.04		3.61 (0.000)
Pseudo firm-fixed effects and year dummies			
Pseudo-fixed effects	0.59		11.88 (0.000)
Year dummies	Yes		
Constant	2.00		4.47 (0.000)
Log likelihood	−39,167.58		
Hypotheses tests			
	χ^2	(Prob > χ^2)	Answer
H1	15.96	(0.000)	Yes
H2 all collaborations	7.37	(0.007)	No (reduced benefit)
Collaborations without internal stars	7.61	(0.006)	Yes
H3	13.41	(0.000)	Yes

Notes: All models have 406 observations. p-value of robust standard errors in parentheses.

TABLE A7 Academic star collaboration in basic research and firms' innovation performance: Omitting 3 firms without star collaboration

		Coef.	*z*-value (*p*-value)
Key variables			
Log (R&D)		0.22	3.64 (0.000)
Basic research publications/R&D		0.04	0.88 (0.380)
Basic research co-publications with academia/Basic research publications		1.06	3.23 (0.001)
Share of basic research co-publications with academia			
... without internal star and without academic stars		Reference group	
... without internal stars and with academic stars			
... which are dedicated and translational	β_{1a}	2.08	3.52 (0.000)
... which are dedicated and non-translational	β_{1b}	1.18	1.35 (0.178)
... which are non-dedicated and translational	β_{1c}	0.41	0.39 (0.694)
... which are non-dedicated and non-translational	β_{1d}	−2.04	−3.00 (0.003)
... with internal stars and with academic stars			
... which are dedicated and translational	β_{2a}	−6.54	−1.84 (0.066)
... which are dedicated and non-translational	β_{2b}	8.33	2.60 (0.009)
... which are non-dedicated and translational	β_{2c}	−10.37	−4.15 (0.000)
... which are non-dedicated and non-translational	β_{2d}	−4.69	−4.26 (0.000)
...with internal stars and without academic stars		0.02	0.03 (0.977)
Firm controls			
Technological diversity		0.01	0.06 (0.949)
Technological diversity^2		0.00	−0.63 (0.527)
Research alliances/R&D		0.23	0.50 (0.615)
Dummy (presence of internal star)		0.13	1.15 (0.251)
Log (firm age)		0.33	3.20 (0.001)
Firm research quality		0.00	−1.59 (0.112)

TABLE A7 (Continued)

	Coef.		*z*-value (*p*-value)
Firm research diversity	−0.90		−0.26 (0.798)
Stars controls			
Research quality of academic stars	0.00		−1.43 (0.152)
Research diversity of academic stars	0.57		1.37 (0.170)
Star-firm collaboration controls			
Quality of basic collaborations with academic stars	0.17		2.78 (0.005)
Experience between firm and academic stars	0.05		3.59 (0.000)
Pseudo firm-fixed effects and year dummies			
Pseudo-fixed effects	0.52		10.15 (0.000)
Year dummies	Yes		
Constant	1.43		3.06 (0.002)
Log likelihood	−25,971.13		
Hypotheses tests			
	χ^2	(Prob > χ^2)	Answer
H1	14.76	(0.000)	Yes
H2 all collaborations	10.13	(0.002)	No (reduced benefit)
Collaborations without internal stars	6.00	(0.014)	Yes
H3	15.83	(0.000)	Yes

Notes: The model has 387 observations. *p*-value of robust standard errors in parentheses.

List of sample companies

Table A8 lists the firms included in our sample.

TABLE A8 Firms included in the sample

Company name	R&D expenditures in 2002 in million US dollars	Headquarter location
Abbott Laboratories	1561	US
Ajinomoto	215	JP
Allergan	233	US
Altana	347	EU
Astrazeneca	3047	EU
Aventis	3218	EU
Barr Laboratories	75	US
Becton Dickinson	220	US
Boehringer Ingelheim	1227	EU
Bristol Myers Squibb	2217	US
Dade Behring	28	US
Daiichi Pharmaceutical	440	JP
Dainippon Pharmaceutical	121	JP
Egis Pharmaceuticals	194	EU
Eisai	476	JP
Eli Lilly	2149	US
Fujisawa Pharmaceutical	497	JP
Galen	19	EU
Gedeon Richter	35	EU
Glaxosmithkline	4360	EU
Guerbet	21	EU
Ipsen	122	EU
Ivax	1	US
Johnson & Johnson	3956	US
Kissei Pharmaceutical	108	JP
Kyowa Hakko Kogyo	233	JP
Lundbeck	190	EU
Merck Co	2677	US
Merck KGaA	572	EU
Mitsubishi Pharma	401	JP
Mochida Pharmaceutical	69	JP
Mylan Laboratories	58	US
Novartis	278	EU
Novo Nordisk AS	499	EU
Ono Pharmaceutical	242	JP
Pfizer	5175	US
Pliva	64	EU
Recordati	33	EU

TABLE A8 (Continued)

Company name	R&D expenditures in 2002 in million US dollars	Headquarter location
Roche	3022	EU
Sankyo	691	JP
Sanofi Synthelabo	1146	EU
Santen Pharmaceutical	101	JP
Schering	891	EU
Schering Plough	1424	US
Schwarz Pharma	116	EU
Seikagaku	29	JP
Sepracor	243	US
Shionogi	249	JP
Shire Pharmaceuticals	201	EU
Skyepharma	46	EU
Stada Arzneimittel	15	EU
Taisho Pharmaceutical	235	JP
Takeda Chemical	990	JP
Tanabe Seiyaku	186	JP
Teva Pharmaceuticals	163	IL
UCB	246	EU
Watson Pharmaceuticals	81	US
Wyeth	2080	US
Yamanouchi Pharmaceutical	533	JP
Zambon	27	EU