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The performance effects of basic research collaboration with star scientists: translation and exclusivity

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Abstract

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State of the art

Prior research has characterized star scientists as extraordinary contributors to their domain and carriers of immense human and social capital (Jaffe 1986; Murray 2004). Even though most star scientists are employed at universities (Zucker et al. 1998), firms may benefit from their unique knowledge through research collaboration (Hess and Rothermael 2011; Zucker et al. 2002). Prior studies have suggested that basic research both performed in-house and in collaboration with universities can improve firmsâ?? innovation performance (Gambardella 1992, Cockburn & Henderson 1998; Leten et al. 2011; Cockburn & Henderson 1998). Performing basic research in collaboration with academic star scientists has however only received limited attention (Zucker et al. 2002).

Research gap

While Zucker et al. (2002) show a positive correlation between the number of star scientist collaborations and the innovation performance of firms, little is known about the conditions under which star-firm collaboration provides the highest benefits to firms. This paper sheds light on collaboration conditions by considering firm-heterogeneity in the relationship between innovation performance and collaboration, by investigating the performance effect of star scientistsâ?? involvement in applied research alongside the joint basic research and by investigating the performance effect of exclusive access to the star scientist.

Theoretical arguments

In this paper we develop three propositions. First, we expect that collaboration with star scientists shifts the performance distribution up primarily for high performing firms, that possess the best capabilities to translate research results into innovations. Second, an academic star who also has experience in applied work will be a higher-valued partner of firms, as her capability to bridge between industry and academe (Baba et al. 2009, Rothaermel & Hess, 2007) enables her to be instrumental in the transformation of scientific discoveries into inventions with commercial value. Third, ensuring exclusive access to the star scientist may be of strategic importance for the firm as the star scientist is considered a crucial resource of knowledge and first access to knowledge is important to establish a lead in technology development (Rothaermel & Hess, 2007). Firms can rule out or at least reduce knowledge spillovers to rival firms if, during their collaboration, the star scientist only cooperates with the focal firm. Hence, we hypothesize that star scientist collaboration has a positive but unequal effect on firmsâ?? innovative performance which is reinforced in a collaborative context of translational capabilities and exclusivity.

Method

We develop a panel data set (1995-2003) on the patent and publication activities of 149 leading firms in the pharmaceutical and biotechnology industry. Innovation performance is measured by citation weighted patent counts while quantile regression analysis uncovers potential unevenly distributed effects. We determine firmsâ?? collaboration with star scientists by co-publication activities with academic scientists that have a publication output or citation total in the top 1% of their scientific field. Star scientists are identified after extensive author name disambiguation (Torvik et al. 2005). Translational context is measured by the publication activity of the star in applied research, while exclusivity is measured as the absence of co-publications between the star and competing firms.

Results

Our preliminary results confirm that the benefits of star scientist collaboration are concentrated among the top performing firms in the biopharmaceutical industry - which implies that collaboration reinforces the inequality in innovation performance. We find that this unequal benefit is reinforced if the firm and the star also perform joint applied research and if the firm has secured exclusive access to the university star scientist. Our analysis suggests that improving innovation performance is not only a matter of collaborating with the brightest individuals, it is also crucial to manage the conditions under which this collaboration takes place. â??

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Reaching for the stars
The Contingent Performance Effects of Basic Research Collaboration between Firms and University Star Scientists

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Abstract

Prior research has characterized star scientists as extraordinary contributors to their domain and carriers of extensive human and social capital. This paper explores the role of these university star scientists as firms' key partners in basic research. We explore the conditions under which collaborations in basic research can improve the innovative performance of the collaborating firms. We analyse patent and publication data of 140 R&D intensive European, American and Japanese pharmaceutical and biotechnology firms from 1995 to 2002 and find that the benefits of basic research collaborations with academic star scientists are highly skewed and concentrated among the top performing firms. The innovation premium of star-firm collaborations increases if the star scientist also performs applied research with the focal firm. The benefit of star collaborations, however, diminishes when the scientist works exclusively with the focal firm. These findings do not only confirm the importance of basic research collaboration with star scientists, but also emphasize the key role of collaboration management.

Keywords: basic research, innovation, star scientists, pharmaceutical industry

1. Introduction

A large body of evidence supports the importance of basic scientific research for advancing economic growth and welfare (Mansfield, 1980; Griliches, 1986; Jaffe, 1989; Adams, 1990; Salter and Martin, 2001; Toole, 2012). Basic research can be defined as activities that are directed towards the general advancement of men's knowledge about the physical world, but without specific commercial objectives (Nelson, 1959). Although most basic research is sponsored by governments, and conducted at universities, multiple studies have indicated benefits of basic research for firms. Numerous important technical inventions were the direct result of advances in scientific knowledge resulting from basic research at academia. Mansfield (1995) found that around 11% of firms' new products and around 9% of new processes could not have been developed (or with a substantial delay) in the absence of basic research conducted by universities. Even higher numbers were obtained for the period 1986-1994 (respectively 15% and 11%), suggesting that basic research has increased in importance for industrial R&D over time (Mansfield, 1998).

Firms that perform basic research in-house increase their understanding of the technological landscape in which they search for inventions (Rosenberg, 1990; Fleming and Sorenson, 2004) and improve their absorptive capacity for external research (Gambardella, 1992; Leten et al., 2011). Additionally, prior studies have confirmed that the benefits of in-house basic research are greater when basic research is conducted in collaboration with university scientists (Henderson and Cockburn, 1998; Fabrizio, 2009) and several studies have documented positive performance effects of firm-university collaboration in general (Furman and MacGarvie, 2009; Belderbos et al., 2004 and 2014; Du et al. 2014). Moreover, knowledge interactions between universities and firms have been growing in scale and scope over time (Perkmann and Walsh, 2007; Du et al., 2014). Especially the "star" university scientists, defined as highly productive individuals who are leading researchers in their field, receive special interest from firms (Zucker and Darby, 1996). Zucker et al. (1998) even states that the positive impact of research universities on nearby firms is due to these specific collaborations with star scientists rather than generalized knowledge spillovers of the university (Zucker et al., 1998). In addition, it has been shown that the number of research collaborations between firms and university star scientists has a positive effect on the number and average quality of firm innovations (Zucker and Darby, 2001; Zucker et al., 2002).

While these studies have suggested that collaborating with academic star scientists is likely to result in an improved innovation performance for the firm, little is known about the contingencies for these effects to occur. Since basic research entails large investments and uncertain outcomes, it is crucial to understand which modalities of these partnerships are prone to increase the benefits of star-firm collaborations. This paper contributes to our understanding by investigating two modalities. First, we examine whether star scientists are also experienced in applied research as this enables the scientist to take up a 'translational' role between basic research and technological applications. To succeed in the hard translational step from basic research results to commercial development, it is crucial to understand the two worlds and recognize opportunities to link science and technology. Second, we examine whether the firm may benefit from exclusivity in the collaboration with star scientist as this mitigates the spillovers of what is arguably unique and highly specialized knowledge to rival firms who may free ride on these research efforts. In sum, we expect that the translational character of the scientist and the exclusiveness of the relationship will act as important moderators for the effectiveness of the star-firm collaboration in basic research, as measured by the innovative performance of the firm.

To test our hypotheses, we make use of a panel dataset on the patent and publication activities of 148 leading innovating pharmaceutical and biotechnology firms. The sample firms have headquarters in the United States, EU and Japan and their technological performance is observed over a period of eight years (1995-2002). Information on scientific publications within the PubMed database is used to examine firms' basic research activities and collaborations with university star scientists. Star scientists are identified as individuals leading their field(s) in terms of the number of scientific publications and citations. We use quantile regression analysis to explain firms' yearly innovative performance, measured by citation-weighted patent counts, as a function of basic research collaboration with university stars, accounting for the aforementioned modalities of these partnerships.

The results indicate that, within basic-research collaborations, academic star scientists can generate a performance premium for firms, especially when they have experience with applied research and also collaborate with other firms. In other words, collaborating with 'translational' stars – who also engage in joint applied work, most importantly, with the focal firm – increases the effectiveness of star-firm collaborations. In contrast, exclusivity reduces the collaboration benefits of both translational as non-translational stars, which contradicts our expectations. Allowing the scientist to collaborate with other firms can be beneficial as it increases the stars' willingness to collaborate or by positive information spillovers from the stars' partners to the firm. Additionally, it can be that the positive effect of exclusive collaborations cannot be measured within two years as these projects are more intensive and take more development time. In general, the results indicate that the collaboration management is key within a star-firm collaboration. Within the following section starts this study will be positioned in two related streams of innovation research, i.e. innovation studies on the role of basic research, and the economics of science literature dealing with star scientists.

2. Literature and Background

Basic Research and Firm Performance

The involvement of firms in basic research has been subject to a long debate among economists. Scholars such as Nelson (1959) have argued that firms are reluctant to invest in basic research because its outcomes are highly uncertain, suffer from appropriability problems and only become apparent in the long run. More recent contributions argue that firms can, nevertheless, be motivated to perform basic research (Rosenberg, 1990; Gambardella, 1992; Fleming and Sorenson, 2004; Cassiman et al., 2008). Firms are, for instance, motivated by the guidance that basic research provides within the technological landscape in which they search for inventions (Gambardella 1992). Basic scientific knowledge allows firms to anticipate the results of research experiments without realizing them, helping to prioritize research avenues and to avoid costly research trials that lead to low-value outcomes (Rosenberg, 1990; Fabrizio 2009; Fleming and Sorenson, 2004; Cassiman et al. 2008). Another motive mentioned in the literature is a more accurate and encompassing perception of the outcomes and implications of applied research (Rosenberg, 1990). Firms are also motivated by the absorptive capacity that in-house basic research generates. The developed knowledge and skills are crucial to understanding and utilizing the findings of basic research conducted elsewhere, most notably at universities (Gambardella 1992, Leten et al. 2011). Finally, firms can be motivated by the increased likelihood to attract academic collaboration partners (Liebeskind et al., 1996) and scientific employees, who highly value basic research and publishing (Henderson and Cockburn, 1998; Hicks, 1999).

Reinforcing these theoretical arguments of motivation, multiple empirical studies (e.g. Gambardella, 1992; Leten et al., 2011, with the exception of Lim, 2004) have found positive performance effects of conducting in-house basic research. Using samples of US pharmaceutical firms, Gambardella (1992) and Cockburn and Henderson (1998) found that firms which perform more basic research, measured by the number of firm publications, produce a greater number of patented inventions. Similar findings were obtained by Leten et al. (2011), using a global sample of pharmaceutical firms and a more accurate indicator of basic research, i.e. the number of publications in basic research journals. In contrast to these studies, Lim (2004) found no effect of in-house basic research on the patent performance of pharmaceutical firms, and even a negative effect for semiconductor firms.

Moreover, studies have found that the benefits of performing in-house basic research are greater when basic research is conducted in collaboration with universities (Cockburn and Henderson 1998, Fabrizio 2009, Leten et al. 2010, Zucker et al. 2002). As it is a Sisyphean task for a firm's R&D-department to remain up-to-date with all the relevant scientific advances, university partners are recommended to provide guidance to and expertise in relevant research areas (Cassiman and Veugelers 2006). The tacit knowledge and preliminary research of academic partners can help firms to fill up the large informative wholes in journal articles (Arora and Gambardella 1990, Cockburn and Henderson 1998) and to build faster on the latest basic research findings in their own applied research activities (Fabrizio, 2009).

University Star Scientists

Within the literature on economics of science, studies have demonstrated a highly skewed distribution of research output across scientists. This is a robust research finding dating back to Lotka (1926), who found that the number of scientists producing n papers is inversely proportional to n^2. Hence, only a small group of scientists, later named star scientists, are responsible for a disproportionally large share of research output. While scholars have recognized that the extraordinary research productivity of scientists depends on a host of individual and institutional factors (e.g. Kelchtermans and Veugelers, 2011), Zucker et al. (1998) found that most star scientists are employed at knowledge institutes and universities: 97.6 % of the stars within Genbank were affiliated to a university or research institution. Scholars have indicated that scientists are reluctant to commit themselves full-time to a firm, as it may impede publishing and actively contributing to the scientific field (Murray, 2004; Stern, 2004). From the perspective of an innovating firm, this academic focus and the scarcity of high-quality scientists implies that research collaboration is of strategic importance to access the best human capital (Hess and Rothermael, 2011; Zucker et al., 2002). Beside high human capital, star scientists also have large collaboration networks. In a pharma and biotech industry, Hess and Rothaermel (2012) found that stars have many connections to non-stars and serve as scientific hubs in collaboration networks. Although star scientists made up only a small portion of the scientist population (<1%), in biotech (pharma) 13% (27%) of non-star scientists have coauthored with star scientists (Hess and Rothaermel, 2012). A limited set of studies have already shown that the number of research collaborations between firms and academic star scientists has a positive effect on the quantity and average quality of firm innovations (Zucker and Darby, 2001; Zucker et al., 2002). However, these studies did not distinguish between collaborations in basic and applied research, and did not study the collaborative context in which basic joint-research between academic star scientists and firms is most effective.

3. Hypotheses

Star-Firm Collaborations (baseline hypothesis)

Basic research collaborations are expected to be beneficial for firms in several ways, especially if they collaborate with academic star scientists. First, partnerships with star scientists grant firms access to scientists with extraordinary research capabilities who are leading their fields in terms of quantity and quality of research outputs (Zucker et al., 1998, 2002). Access to extraordinary scientists is important in basic research since basic research is a complex activity, which is characterized by high levels of uncertainty. Collaborations with star scientists often lead to extensive debate, exchange of ideas and discussions. This provides firms with access to tacit knowledge of star scientists (Cockburn and Henderson, 1998) and codified scientific research of stars that is not yet published (e.g. work in progress), allowing firms to build faster on recent basic-research findings in their own applied research (Fabrizio, 2009).

Second, collaborations with star scientists provide firms access to their large scientific networks (Hess and Rothaermel, 2012), and so provide useful contacts, recognition and wider knowledge spillovers (Murray, 2004; Luo et al., 2009). Finally, the academic star scientist may strengthen the firm's absorptive capacity for basic research by helping it to recognize and understand advances in basic scientific research (Cockburn and Henderson, 1998) and further enhance the research capabilities of the firm's R&D department improving the overall quantity and quality of research conducted in the firm. This results in the following baseline hypothesis on the involvement in basic research with star scientists.

H_0: Collaboration with academic star scientists in basic research improves the innovative performance of firms.

Translational Star Scientists

Building on prior research into the obstacles of effective university-industry collaborations (e.g. Bruneel et al., 2010), we argue that bridging between the deep scientific capabilities of star scientists and the more applied research of firms is not trivial and depends on the 'translational' character of the star scientists. The way academic star scientists approach science is strongly driven by their taste for science and the priority-based scientific reward system (Merton, 1957; Dasgupta and David, 1994). This strongly contrasts with the profit-seeking way in which firms deal with science (Rosenberg, 1990; Arora and Gambardella, 1994). Scholars have considered this different research aim, and the resulting distinctive capabilities, as the basis for a division of labor in the innovation process, where one party specializes in 'invention' while the other focuses on 'innovation' (Arora and Gambardella, 1994). However, as Arora and Gambardella (1994) argue, division of labor poses greater challenges in innovation than in (for example) manufacturing since knowledge is difficult to transfer in arm-length relationships. This difficult transfer is illustrated by the high 'fall-out-rate' when translating scientific breakthroughs to industrial application: it takes on average 17 years for only 14% of new scientific discoveries to enter day-to-day clinical practice (Westfall et al., 2007). Our analysis ties into this issue and contributes to understanding the extent to which deliberately avoiding a clear-cut role division and involving the star scientist in applied research, pays off for the firm.

The idea that scientists may engage in applied research jointly with firms departs from the stereotypical view that scientists are only interested in basic research and publishing. Recent studies in the science literature have indicated that there are scientists who have a preference to also do applied work (Stokes, 1997; Sauermann and Roach, 2012; Sauermann and Stephan, 2013). Moreover, multiple researchers have indicated that there is a two-way interaction between basic and applied research (Rosenberg, 1990, Sauermann and Roach, 2011). Just like basic results can lead to follow-up applied research, scientists can detect new and promising directions for basic research when performing applied work. Meyer (2006) found that the publication output and quality of scientists that both publish and patent is higher than those that specialize in one activity. In short, it is certainly possible that scientists are willing to complement basic research collaborations with joint applied research as it may fall within their interest and it may even improve their performance in basic scientific research.

In this respect, we expect that the university star scientist can play a pivotal role for the firm's innovative performance by being involved in applied research and this for two reasons. First, a scientist that is active in both basic and applied research will be able to bridge the two distinct worlds (Gittelman and Kogut, 2003; Rothaermel and Hess, 2007; Baba et al. 2009; Subramanian et al., 2013). Gittelman and Kogut (2003) stress that the selection criteria for an important scientific invention follow a different logic than the criteria for a valuable innovation in the commercial world. A 'translational' scientist is capable to assess both sets of criteria and to discover new opportunities to connect science and technology. Second, scientists possess knowledge that is valuable within the development process and that cannot be retrieved from descriptions in scientific publications that report on their basic research (Agrawal, 2006; Sorenson, 2006; Fuller and Rothaermel, 2012). Scientists contribute insights, experience, behavioral practices and memory of trial and error. Even if basic research was conducted jointly, its full value may not come to surface without involving the scientist in development activities (Sorenson, 2006). It follows that collaborative basic research with a 'translational star' – an academic star scientist who is, next to basic research, also involved in applied work with firms - generates a premium upon firms' innovative performance.

H_1: The innovation premium of star-firm collaborations in basic research increases if the academic star scientist is also involved in applied research.

Exclusive Access to Star Scientists

The star scientist can be seen as a crucial resource within the innovation process, giving direct access to unique scientific knowledge (Rothaermel and Hess, 2007). However scientific knowledge is believed to be partly a public good and therefore freely available to other firms (Arrow, 1962; Nelson, 1959). Consequently, the collaborating firm will seek to prevent the knowledge from spilling over to competitors who can then free ride on its investment (Sorenson, 2006). In particular, rival firms engaged in parallel research projects with the same academic scientist may get access to the scientist's expertise, even under contractual limitations on sharing certain pieces of knowledge.

Fortunately, knowledge is not a pure public good, available to everyone. As scholars have indicated, scientific knowledge is not a ready-made input (Gittelman and Kogut, 2003). Learning and understanding scientific results requires time and absorptive capacity, i.e. in-house experience in basic research (Cohen and Levinthal, 1989; Kittelman and Kogut, 2003). Further, the knowledge necessary to develop a new technology may (still) be embedded in the inventor as it is tacit or not yet been codified (Zucker et al., 1998). In short, firms will experience difficulties when entering a new technology and these difficulties will drop in time and with proximity to scientific discoverers (Zucker et al., 2002). Consequently, when a star scientist exclusively collaborates with the focal firm, the firm will be able to temporarily safeguard unique access to scientific knowledge and obtain a first mover advantage in knowledge. Even if the basic research findings are published, the lack of required tacit knowledge will make it difficult for competitors to put the basic results to productive use (Cohen and Levinthal, 1989), and the firm can still obtain a crucial first-mover advantage in the development phase (in particular if this culminates in a patent application).

Besides the strategic protection against competitors, an exclusive connection with the star scientist can also directly affect the quality of joint research. One direct effect is the greater availability of the star scientist, which can result in more intense and frequent interactions. Second, the firm and the scientist will obtain a more open collaborative relationship as it is free from outsiders. The firm will be more willing to share valuable trade secrets and the star scientist may be less restricted in her communication due to secrecy agreements stemming from other projects. The resulting higher levels of trust will lead to a more fluent interaction, and the freedom to talk will lead to a larger scope of subjects and directions of research to be discussed. In turn, the increased quality of the interaction will reinforce the success rate of the collaboration (Bruneel et al., 2010; Tartari et al., 2012; Forti et al., 2013; Plewa et al., 2013). From the above considerations, it follows that the performance effect of star-firm collaborations in basic research are more pronounced if the firm has secured (temporary) exclusive access in research to the academic star scientist.

H_2: The innovation premium of a star-firm collaboration in basic research increases if the firm has secured exclusive (temporary) access to the star scientist.

4. Data and Empirical Model

Sample firms

To answer the proposed research questions, we constructed an extensive panel dataset on the patent and publication activities of 140 pharmaceutical and biotechnology firms in 1995-2002. The firms have headquarters in the United States, the EU or Japan and are among the largest R&D spenders (in absolute terms) in the pharmaceutical industry.[1] The sample is slightly unbalanced due to merger activity after the first year of observation. For example, AstraZeneca was formed in 1999 by a merger of the firms Astra and Zeneca, and is included in the panel dataset from 2000 onwards. Our hypothesizes will be tested on these firms by explaining the firms' innovative performance by its publication portfolio.

Patent data

The firms' innovative performance is based on patent data. Patent indicators lend themselves to empirical analysis for multiple reasons (Pavitt, 1985; Basberg, 1987; Griliches, 1990). First, patents contain detailed information on the technological content, owners and prior art of patented inventions. Further, patent data are objective in the sense that they have been processed and validated by patent examiners, and finally, they cover long time series. Like any indicator, patent indicators are also subject to a number of drawbacks, the principal ones being that not all inventions are patented and those that are patented vary in their technical

[1] As reported in the 2004 EU Industrial R&D Investment Scoreboard. This ranking lists the top 500 corporate investors in R&D whose parent is located in the EU, and the top 500 companies whose parent is located outside the EU (mainly US and Japan), based on corporate R&D expenditures in 2003.

and economic value (Trajtenberg, 1990; Lanjouw et al, 1998; Gambardella, 2008). The first problem can be addressed by limiting patent analyses to industries with high patent propensities and studying firm-level patent time series. The 'value problem' can be taken care of by weighting patent counts by the number of forward patent citations (Trajtenberg, 1990; Harhoff et al, 1999).[2] Both approaches are followed in this paper.

Another methodological issue related to using patent data in a firm-level analysis is that company names in patent databases are not unified and patents may be applied for under names of subsidiaries or divisions of a parent firm. Therefore, patent data have been 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 included 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', were used. The consolidation was conducted on a yearly basis to take into account changes in the group structure of sample firms due to acquisitions, mergers, green-field investments and spin-offs. Acquisitions, and their patent stocks, are considered part of a parent firm from the year the acquisition transaction has been completed.

The innovative performance of the sample firms, our dependent variable, is yearly measured by the citation weighted patent count (Trajtenberg, 1990) of a parent firm in a year. Patent data is extracted from on the PATSTAT database (2011), which contains information for patents from all major patent offices worldwide (EPO, USPTO, JPO) and a large set of national patent offices. We apply a fixed 4-year window to calculate the number of citations that patents receive in order to establish a comparable citation window across patents (Hall et al, 2005; Trajtenberg, 1990). All patent data is gathered at the consolidated firm level and corrected for DOCDB patent families (Martinez, 2011). For the calculation of citation counts, both the citing and cited patents are corrected for DOCDB families to avoid double counting patents on similar inventions. Finally, we only consider patents within the IPC classes of 'Instruments' and 'Chemistry' (Schmoch, 2008) which forms a broad coverage of the life science industry. Because some of the sample firms are highly diversified and the publication

[2] In particular in the pharmaceutical industry, patents and patent citations are a relevant indicator of innovative performance and closely linked to market valuation (Hall et al., 2005). Magazzini et al. (2012) show that patents protecting chemical compounds that successfully get through clinical trials get significantly more citations than patents pertaining to compounds that fail in initial trials (but often get a second life in another application), while patented compounds that do not make it to such trials receive no or less citations.

data, discussed in detail in the next section, are extracted from PubMed, a database of life science publications, restricting the patent data aligns the field of observation on both sides of the regression.

Publication data

While the patent data of the focal firms proxies innovative performance, the publication data, which is extracted at the consolidated firm level from PubMed, represents both scientific activity and collaborative behavior. Publication counts represent investment levels in science and proxy for the extent to which companies are involved in the scientific community (Gambardella, 1992, 1995). In addition, publication rates are a timely measure of firms' involvement in basic research since the turn-around time of publications in most exact sciences fields is short (Kaplan et al, 2003). To approximate scientific activity even more accurate, we focus on publications in basic research journals, using the CHI journal classification scheme which classifies journals in different levels, from applied to basic research (Hamilton, 2003; Thursby and Thursby, 2011; Leten et al., 2011).

While publication counts signal general scientific activity, co-publications with academia indicate university-industry collaborations. While university-industry interactions may also occur through other channels[3], prior research has validated a co-publication as a reliable indicator of collaborative research (Cockburn and Henderson, 1998; Fabrizio, 2009; Leten et al, 2011), especially of collaborations with joint formulation of the research problem as well as joint realization of the research activities (Laudel 2002). In the study of Melin and Persson (1996), only five percent of the surveyed scientists reported instances of collaboration not resulting in co-authored papers. Additionally, a study of European and Japanese firms in the electronics and pharmaceuticals sectors concluded that the largest majority (84-93%) of co-publications involved at least some sort of collaboration (Hicks, 1996). In sum, most collaborations result in co-authored publications, and most co-publications do reflect actual research collaborations. In our publication data, we identify academic co-authorship by a string-matching algorithm that recognizes affiliations of universities or research institutions.

[3] See Schartinger et al. (2002) for a comprehensive study on forms of knowledge exchange including citations of university publications in firm publications or patents and contract research.

Academic Star Scientists

After determining the university-industry collaborations, we further disentangle the firm's publications to co-authorship of an academic star. The challenging task of disambiguating authors is accomplished by the Authority dataset of Torvic and colleagues (Torvic et al., 2005; Torvic and Smalheiser, 2009), who have uniquely identified authors on PubMed publications until 2009. Consequently, the authors of our firms' publications can be compared with all authors within PubMed on the basis of their complete publication portfolio (publication and citation count) in PubMed. In contrast to most prior studies of star scientists, we compare scientists within each scientific field separately to control for discipline-specific publication and citation patterns (e.g. Kelchtermans and Veugelers, 2013). Based on the journal categorization of Thomas Reuter (2014), we consider 44 distinct fields across the larger scientific domains of 'Medicine' and 'Life Sciences'. If the scientist has, in at least one of these fields, a publication count or citation count that exceeds the field's mean plus 3 standard deviations, she is considered a star scientist (Rothaermel 2007, 2012). Additionally, this star identification is applied dynamically through a moving 4-year window of publication and citation counts. Consequently a scientist can become a star during the period of interest (1991-2002), but can also lose their star label, for instance, due to retirement or career changes. While a dynamic identification has been described by Hess and Rothaermel (2012), it has, to our knowledge, never been utilized within a regression analysis.

In total we compare 2,100,593 scientists with at least one publication in 'Medicine (2,078,111 scientists) or 'Life Science' (97,287 scientists), resulting in 162,894 star scientists. For the co-authors of our firms (245,539), this dynamic and within-field comparison of scientists comes down to 41,501 star scientists. Of these scientists, 80% (33,275) retains their star label in subsequent years, which supports the idea of persistency of extraordinary performance mentioned in prior studies (eg. Kelchtermans & Veugelers, 2011).

However not all the identified stars are employed at a research institution or university. To distinguish star scientists that work in academia from those in the corporate world, we applied specific string-algorithms on three forms of affiliation data: the first-author addresses within the scientist's publications, email-addresses and addresses listed on the publications of our firms. The latter is retrieved from the WoS where complete address lists are provided with each publication. Unfortunately these lists lack a one-to-one link with the authors resulting in an overarching rule: "If a scientist has at least one publication on which only corporate addresses are listed, this scientist most have been employed in industry." However this single rule is inconclusive to determine the main affiliation as academic scientists can have a temporary position at industry and as scientists at firms may always publish with universities. Hence, the rule is complemented by the affiliation information of the first author and the email-addresses which are both uniquely linked to the author respectively within PubMed and the Authority dataset (Torvik et al., 2005; Torvik & Smalheiser, 2009). In line with previous studies who stated that most star scientists are employed at academia (Zucker et al., 1998), our methodology recognizes 33,541 (81%) academics among the 41,501 star scientists. This procedure results in 28,828 publications of our firms that are co-authored by an academic star scientist (being identified as star in the year of the publication). Now that we have identified the academic star scientists, we can explore their translational and exclusive character.

The translational character of a scientist is determined by the ability to understand applied research and link basic research to commercialization. An academic scientist, who is already strongly familiar with basic research, can obtain this ability by experience in applied research, most particularly, through collaboration with a firm. By performing applied research, the scientist gets acquainted with different terminology and methods and by collaboration with firms in this research it obtains tacit knowledge on commercialization and even specific knowledge of the operations and products of the firm. In line with this understanding of a translational character, we utilize two different measurements of translational scientists within our analyses. The first measurement takes a broad perspective by considering all co-publications of the scientist with one of our sample firms. We state that a scientist is 'broadly translational' in year t if, in t or t-1, she has at least one applied publication[4] co-authored <u>with a sample firm</u>. The second measurement focuses on the knowledge interaction between the scientist and one specific firm, the focal firm. The assumption behind this measurement is that the scientist will only be able to show translational skills for the focal firm if she understands the operations, methods and products of that specific firm. Consequently, for this measurement, we state that a scientist is 'focused translational' in t if, in t or t-1, she has at least one applied publication in collaboration <u>with the focal firm.</u> Hence, 'focused translational' star scientists form a subset of 'broadly translational' star scientists.

The exclusive character of a star scientist is determined vis-à-vis a certain, focal firm and is defined as the absence of co-publications of the star with another firm of our sample. As the

[4] As mentioned before, all the publications of our sample firms are categorized from basic to applied according the CHI-journal classification.

importance of exclusivity may vary across different collaboration forms, two measurements with a different focus will be applied. The first measurement takes a broad view by defining a star-firm relationship in year t as exclusive when the star scientist has not one co-publication with another firm in year t or t-1. The second measurement takes a narrow view by defining a star-firm relationship in year t as exclusive when the star scientist has no basic co-publication with another firm in year t or t-1. Note that the second measurement forms a subset of the first measurement.

After determining the academic star scientists and their characteristics, every publication of our sample firms are categorized under the different collaboration forms and, in turn, aggregated to the firm-year level. In the empirical analysis, collinearity between the collaboration variables is avoided by defining each form of collaboration in a relative way, rather than as an absolute count of publications. More specifically, the 'hierarchy' of collaborations is composed of the following categories: basic research collaboration with academia → with academic stars → with (non-)translational stars → in exclusivity with (non-)translational stars. In terms of variable definition this means that, for example, collaboration with translational stars is measured as the number of basic research publications with translational stars divided by the number of basic research publications with (both translational and non-translational) stars.

Descriptive Statistics & Empirical Methodology

A key feature of the data is that the technological performance distribution is very skew, with a few firms applying for a high number of (citation-weighted) patents every year, while the bulk of firms show a (relatively) more modest output.[5] To further illustrate this, Figure 1 relates the distribution of technological performance, measured by the citation-weighted patent output of firms in year *t*, to firms' involvement in basic research in years (number of publications in basic science journals from t-4 to t-1 divided by million US dollars of R&D expenditures). A few firm-year observations have been highlighted to illustrate heterogeneity among firms. For example, Biogen Idec innovates at a lower rate than the much larger Roche. Note that we will control for firm size in the regression analysis. Finally, the vertical axis on the right of the graph shows firms' share of basic research with academic scientists and with

[5] The average number of yearly citation-weighted patents across firms is 290, but with a very large standard deviation of 576.

academic stars. While both remain fairly stable across the performance distribution, it is noteworthy that also the smaller and/or less productive firms engage to the same extent (in relative terms) in collaboration with stars, if not more. This is a first indication that innovative performance does not solely depend on the fact *whether* a firm collaborates with a star and that ‘how’ one collaborates may be of significant importance.

The highly skewed performance distribution calls for an appropriate empirical approach. In particular, the clear departure from normality suggests that the most salient insights in the data may remain below the radar if one only considers the effects of covariates on the conditional mean of performance. Therefore, we employ quantile regression analysis, which allows estimating the effects of the collaboration variables on different quantiles of the performance distribution. Since the dependent variable (citation-weighted patents) is discrete, we use Machado and Santos Silva’s (2005) technique of imposing artificial smoothness (‘jittering’) to allow for consistent estimation of the quantile parameters. Accordingly, Table 1 further exposes the variation across the performance distribution by reporting the ‘localized’ means of the covariates i.e. including those observations that fall within a given percentile range of innovative performance. Within this table, the translational and exclusive character of stars are determined on a moving two-year publication portfolio (t and t-1) and are respectively calculated in respect to all firms and all publications. The table also introduces the control variables that will be included in the regression analysis: R&D expenditures (log in t-1), involvement in basic research (number of basic research publications $_{t\text{-}1 \text{ to } t\text{-}4}$/R&D $_{t\text{-}1}$), the share of joint basic-research with university (from t-1 to t-4) and dummies for biotechnology and instrumental companies. Instrumental firms are located in a market that is less basic research intensive then pharmaceutical or biotechnology. Within the correlation matrix shown in table 2, this is clearly indicated by the negative correlations between the instrument dummy and all the innovation activities. Also, biotech firms operate within a different market than pharmaceutical firms. They do not have stable revenues from mass-production drugs resulting in lower R&D expenses, higher reliance on innovation and more risk taking. Additionally, we will control for the extent of R&D expenses, as firms with a large and diversified set of R&D projects may have more opportunities to benefit from the star’s knowledge. Further, we incorporate the amount of in-house research of the firm by accounting for its publications in basic journals.

5. Empirical Results

Like the descriptives section, the first part of this results section will focus on the broadest identification of the translational and exclusive character of the star scientist. More precisely, a star scientist is translational if the star has at least one applied publication with one of the sample firms in t or t-1. Additionally, a star-firm collaboration is exclusive under the absence of any publication between the star scientist and another sample firm (in t and t-1). Table 3 presents the coefficients of the variables explaining citation weighted patent count within a quantile regression containing 5 quantiles of the dependent variable (25%, 50%, 75%, 90%, and 95%).

First, note that the control for firm size (log of R&D expenditures) is associated with a higher technological performance throughout the distribution. The quantile regression shows the complex relation between internal basic research and collaborations with universities. The results reveal that the effect of collaboration is of greater magnitude than the effect of basic science intensity, in particular at the higher end of the distribution. For instance, in quantile 95, the effect of university-industry collaborations is substantial with a marginal effect of 299 (evaluated at local means), or 1,63 standard deviations. In contrast, the marginal effect of basic research intensity even turns negative at this point (-7), indicating that high-performing firms may only benefit from additional basic research if performed in collaboration with universities. Note that the highest-performing firms (p95 and higher) are not the most basic research intensive companies (see Table 1). Moreover, the quantile regressions show that star scientists generate a performance premium to university-industry collaborations, namely within the upper quantiles of 90% and 95% (only significant under a translational and exclusive collaboration). While this result indicates a positive effect of star-firm collaborations for some firms, not every firm is able to benefit from the stars' extraordinary capabilities. This results does not only support our baseline analyses, it also recognizes the idea of unequal benefit mentioned in prior literature. In this respect, studies have referred the the importance of absorptive capacity to evaluate, understand and integrate scientific frontier knowledge, or skills in translating insights from basic research into applied and clinical research, and ultimately new inventions (Cohen and Levinthal, 1989 and 1990; Cassiman and Veugelers, 2006; Fabrizio, 2009). These differences in firms' endowments have implications for their ability to learn from external research findings.

The coefficients of the remaining collaboration variables are only significant within quantiles 90 and 95 and will be further discussed by means of table 4. This table presents these quantiles within four different models, each using a different measurement of the translational (broad or focused) and exclusive (only in basic research, in basic & applied research) type of star scientist. The remarkably different results of these four models indicate that the method of measurement matters and that there is a strong interaction effect between the two types. While this interaction makes the interpretation of results difficult, interesting findings can be found. Table 4 shows a performance premium of the translational character of the star scientist, although it is sometimes neutralized by the interaction with exclusivity[6]. Moreover, a star that is 'focused translational' generates a higher performance premium than a 'broadly translational' star scientist. Hence it is not only important that the star has experience in applied research, it is key that she obtains this experience with the focal firm. However having an exclusive relationship with a translational scientist diminishes this positive effect. Additionally, it is not only important to avoid exclusivity in basic research, exclusivity should also be avoided within applied research. This finding can be noticed by the models with 'exclusivity in basic research only' that show, beside significance of exclusiveness, a strong neutralization of the translational coefficient as it still captures does collaborations with exclusiveness in applied research. Finally, when the star is not translational, an exclusive relationship has a negative effect on innovative performance, except when she still performs some applied research with another firm. The latter case, presented in the bottom left corner of table 4, shows no significant coefficients. While we did not expect a negative effect of exclusivity, three explanations can be mentioned. First, star scientists may be reluctant to collaborate under exclusivity as scientists appreciate freedom and may already have relationships with other firms. Second, exclusiveness may proxy for a collaboration project that is time intensive and highly complex. These large projects demand full commitment of the scientist leading to exclusivity and entail breakthrough science resulting in high risk and long-time frames before patenting. Hence the positive effect of these projects can only be observed at a later point in time. Third, the firm may benefit from the multiple partnerships of the star scientist as information of those partners may spill over to the focal firm. This beneficial spillover may outweigh the negative spillover form the focal firm to the star, which we expected before.

6. Conclusions

Our study has provided a number of important insights into the conditions under which joint basic research with university star scientists improves the technological performance of firms. While the benefits of such collaboration are unevenly distributed across firms, they can increase innovative performance, especially when collaborating with a translational star and, surprisingly, when avoiding exclusivity of the collaboration.

Fundamentally, our research underscores that while a firm may improve its innovative performance by collaborating with the ‘best and brightest’ inside academia, there is a clear managerial challenge to make such partnerships reach their full potential. In particular, the positive effect of working with a translational scientist and, even more, performing applied research at the focal firm, represent handles for firms to build productive partnerships. Widening the scope of collaborations beyond basic research has implications for the search process of the firm, as not every star may have the capabilities for, or be interested in, applied work.

We had expected that exclusivity would harness the positive effects of star collaboration, by increasing trust among and providing a first-mover advantage for the firm, which potentially would help claim patentable inventions. Our preliminary empirical results clearly indicated the opposite: exclusivity reduces the positive effect of basic research collaboration with star scientists. While the specific reason for this negative effect of exclusivity is still unclear, possible explanations are the breakthrough and log-run character of exclusive projects, the reluctance of scientists to be bound to an exclusive relationship and the positive knowledge spillovers from other partners of the scientist to the focal firm.

In future research we aim to refine our analysis in several ways. First we aim to examine the relationships allowing for different lags between collaboration and innovation performance. Second, we aim to include a broader set of controls among which technological diversity and firms’ technology alliances. Third, we can expand our definition of exclusivity to firms outside our sample and we can determine applied experience of the scientist beyond collaborations with firms. Additionally, we will also examine heterogeneity among the current set of stars, by exploring whether there is a premium of collaboration of the top performing stars in the sample – defining top stars as scientists with a publication performance of more than 5 standard deviations above the mean. Finally, we aim to examine the relationship with other indicators of innovative performance, like number of new products in development.

Beyond this work in progress, we advance the following avenues for further research. First, while we believe the results are likely relevant for other science-intensive industries, our findings need to corroborate beyond the life sciences. Further, difficult-to-find information on (part-time) corporate affiliations of stars or their transfer to industry would permit further insights with respect to the precise commitment of the star to translational science. A final issue with implications for external validity is the potential endogeneity of star collaboration. In particular, the 'best' firms - in terms of basic science capabilities, innovation track record, etc. - may be more likely to successfully team up with academic star scientists. Note that our empirical approach does mitigate the issue of selection since the effects that we find occur within the upper end of the distribution, suggesting that the heterogeneity among top performing firms in terms of specific features of basic research collaboration drives performance benefits. Future work providing insights into the matching process between firms and stars would constitute a valuable addition to the results presented here.

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8. Tables and Figures

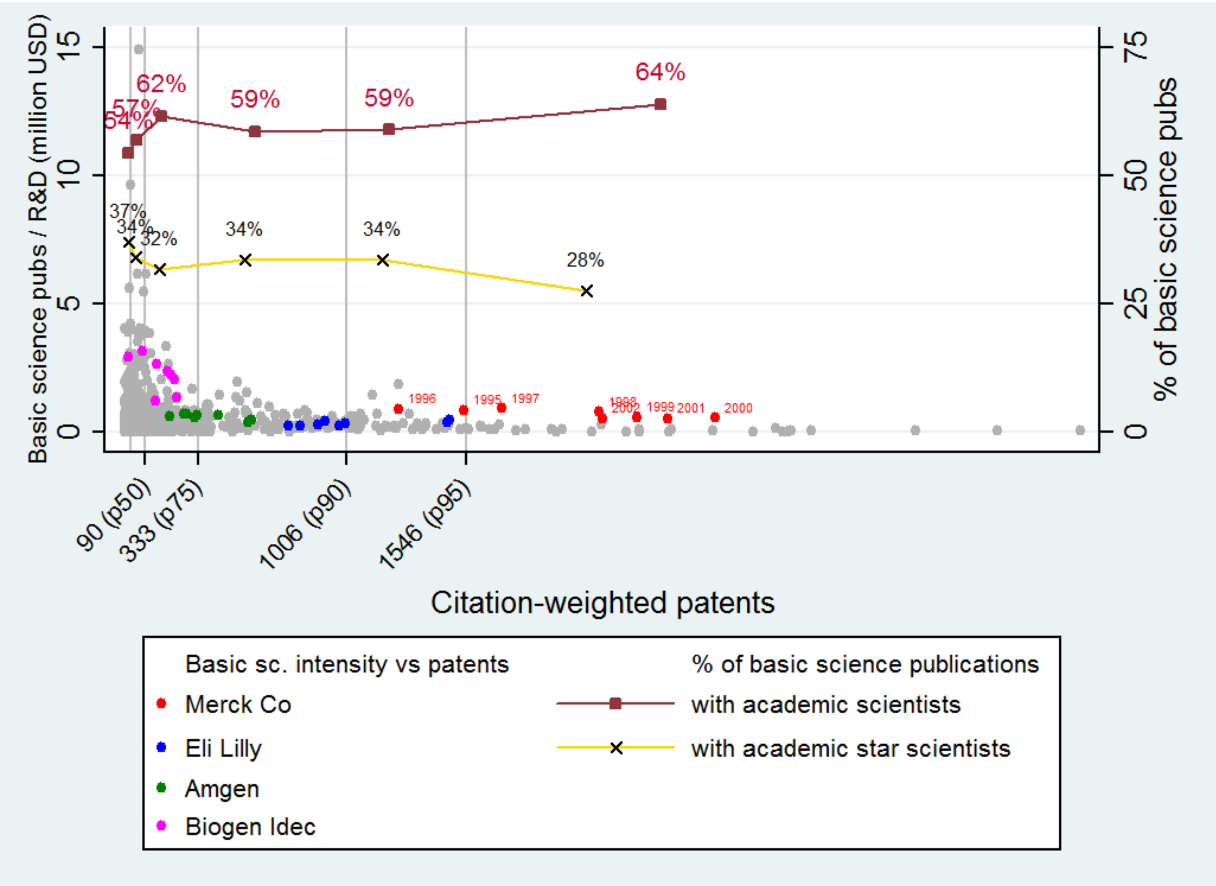

Figure 1: Skewed distribution of citation weighted patent count, firm heterogeneity in basic research intensity and percentage indication of star-firm collaborations

Table 1: Overview of the means of major regression variables per quantile

Variables	Percentiles of citation-weighted patent output i,t p0-p25 Mean	 p25-p50 Mean	 p50-p75 Mean	 p75-p90 Mean	 p90-p95 Mean
Citation-weighted patents$_t$	12.70 (7.36)	40.86 (12.74)	129.89 (52.55)	465.90 (200.63)	1080.81 (183.74)
Log(R&D$_{t-1, \text{Million USD}}$)	9.71	10.14	10.92	12.13	13.62
Basic science pubs$_{(t-1 \text{ to } t-4)}$/ R&D$_{(y-1 \text{ in million USD})}$	9.71	10.14	10.92	12.13	13.62
% with university co-authors $_{(t-1 \text{ to } t-4)}$	0.49	0.82	0.73	0.46	0.35
% with university stars$_{(t-1 \text{ to } t-4)}$	0.53	0.58	0.61	0.59	0.58
% with translational star$^{*}_{(t-1 \text{ to } t-4)}$	0.33	0.42	0.47	0.53	0.53
% in exclusivity$_{(t-1 \text{ to } t-4)**}$	0.18	0.25	0.22	0.28	0.28
% of collaborations with non-trans. star* in exclusivity$^{**}_{(t-1 \text{ to } t-4)}$	0.13	0.20	0.17	0.27	0.31
Dummy biotech firm	0.39	0.51	0.58	0.67	0.76
Dummy instrumental firm	0.65	0.70	0.60	0.45	0.07
N$_{\text{firms}}$***	64	72	76	42	16

In brackets the standard deviation is listed.
*The translational character of a star scientist is determined by at least one applied publication of the star scientist with one of the sample firms in t or t-1.
** The exclusive relationship between a star scientist and a focal firm is determined by the absence of a publication with another sample firm in t or t-1.
*** For the average per percentile band, N$_{\text{firms}}$ indicates the number of unique firms represented in the percentile band. As we have multiple observations of one firm across time (1995-2002), firms may occur in more than one percentile band.

Table 2: Correlation matrix of the regression variables

	1	2	3	4	5	6	7	8	9	10
	Citation-weighted patent count$_t$	Log(R&D$_{t-1}$ in Million USD)	Basic science publications $_{t-1 \text{ to } t-4}$/ R&D$_{t-1}$	Percentage of basic publications in collaboration with academia $_{t-1 \text{ to } t-4}$	Percentage of collaborations with academic stars $_{t-1 \text{ to } t-4}$	Percentage of star collaborations with a translational star* $_{t-1 \text{ to } t-4}$	Percentage of translational-star collaborations in an exclusive relationship** $_{t-1 \text{ to } t-4}$	Percentage of non-translational-star collaborations in an exclusive relationship** $_{t-1 \text{ to } t-4}$	Dummy for biotech firm	Dummy for instrumental firm
1	1.0000									
2	0.6611	1.0000								
3	-0.1172	-0.2690	1.0000							
4	0.0473	0.0607	0.1937	1.0000						
5	0.0764	0.1998	0.1380	0.4907	1.0000					
6	0.0552	0.1197	0.1683	0.2294	0.4034	1.0000				
7	0.1617	0.2075	0.0609	0.2042	0.3135	0.5127	1.0000			
8	0.1652	0.3688	0.2032	0.4153	0.5678	0.1690	0.2574	1.0000		
9	-0.3802	-0.5765	0.2592	0.0420	0.0373	-0.0317	-0.1622	-0.0729	1.0000	
10	-0.1433	-0.1948	-0.0953	-0.1214	-0.1199	-0.1217	-0.1385	-0.2292	0.0897	1.0000

* The translational character of a star scientist is determined by at least one applied publication of the star scientist with one of the sample firms in t or t-1.
** The exclusive relationship between a star scientist and a focal firm is determined by the absence of a publication with another sample firm in t or t-1.

Table 3: Regression results in 5 quantiles

DV: Patent count within 'Instruments' and 'Chemistry' of firm I in year t, weighted by 4-year forward cites	Quantile-Regression Coefficients 25%	50%	75%	90%	95%
Log(R&D$_{t-1, \text{Million USD}}$)	0.96*** (8.68)	0.85*** (14.29)	0.72*** (29.39)	0.59*** (70.79)	0.54*** (287.83)
Basic science publications $_{t-1 \text{ to } t-4}$/ R&D$_{t-1}$	0.24 (1.57)	0.20* (1.93)	0.23*** (13.06)	0.06** (2.06)	-0.01*** (-13.79)
Percentage of basic publications in collaboration with academia $_{t-1 \text{ to } t-4}$	0.01 (0.01)	0.20 (0.69)	0.34** (2.16)	0.52*** (10.76)	0.60*** (8.21)
Percentage of university-industry collaborations with academic stars $_{t-1 \text{ to } t-4}$	0.41 (0.61)	0.32 (0.96)	0.01 (0.14)	0.45*** (10.83)	0.14 (1.21)
Percentage of star collaborations with a translational star $_{t-1 \text{ to } t-4}$*	-0.68 (-1.08)	-0.30* (-1.87)	-0.10 (-0.53)	-0.10 (-0.86)	0.18** (2.54)
Percentage of translational-star coll. in an exclusive relationship $_{t-1 \text{ to } t-4}$**	0.22 (0.15)	0.12 (0.42)	0.32*** (4.57)	-0.10 (-1.35)	-0.48*** (-3.07)
Percentage of non-translational-star coll. in an exclusive relationship $_{t-1 \text{ to } t-4}$**	-0.32(- 0.73)	-0.34(- 1.61)	-0.38*** (-3.25)	-0.55*** (-22.68)	-0.22*** (-5.46)
Dummy for biotech firm	0.43 (0.70)	0.44*** (3.82)	0.22*** (2.71)	-0.15*** (-3.18)	-0.20*** (-5.41)
Dummy for instrument firm	0.09 (0.38)	-0.05 (-0.20)	-0.14** (-1.96)	0.00 (0.02)	-0.05 (-0.88)
_cons	-7.08*** (-5.20)	-4.97*** (-5.68)	-2.79*** (-8.80)	-0.46*** (-4.09)	0.22*** (3.46)
Year dummies included					
N	852.00	852.00	852.00	852.00	852.00

Table 4: Regression results using different measurements of exclusivity and translational

DV: Patent count within 'Instruments' and 'Chemistry' of firm i in year t, weighted by 4-year forward cites	Quantile-Regression Coefficients							
	Broadly translational, exclusive in applied & basic research		Broadly translational, exclusive in basic research only		Focused translational, exclusive in applied & basic research		Focused translational, exclusive in basic research only	
	90%	95%	90%	95%	90%	95%	90%	95%
Log(R&D$_{t-1, \text{Million USD}}$)	0.59*** (70.79)	0.54*** (287.83)	0.61*** (7.27)	0.55*** (53.30)	0.58*** (31.84)	0.53*** (9.88)	0.60*** (8.22)	0.53*** (8.91)
Basic science publications $_{t-1 \text{ to } t-4}$/ R&D$_{t-1}$	0.06** (2.06)	-0.01*** (-13.79)	0.10 (0.13)	0.02 (0.83)	0.05 (1.41)	0.02 (0.45)	0.07 (0.63)	0.08 (0.56)
Percentage of basic publications in collaboration with academia $_{t-1 \text{ to } t-4}$	0.52*** (10.76)	0.60*** (8.21)	0.46 (0.48)	0.51*** (5.62)	0.40** (2.16)	0.53*** (7.20)	0.37 (0.83)	0.40 (0.95)
Percentage of university-industry coll. with academic stars $_{t-1 \text{ to } t-4}$	0.45*** (10.83)	0.14 (1.21)	0.48 (0.32)	0.17 (0.89)	0.41*** (2.91)	0.33** (2.11)	0.39 (0.79)	0.27 (1.64)
Percentage of star collaborations with a translational star $_{t-1 \text{ to } t-4}$*	-0.10 (-0.86)	0.18** (2.54)	-0.15 (-0.10)	0.52*** (3.30)	-0.01 (-0.06)	0.45*** (3.95)	0.02 (0.06)	0.41 (1.01)
Percentage of translational-star coll. in an exclusive relationship $_{t-1 \text{ to } t-4}$**	-0.10 (-1.35)	-0.48*** (-3.07)	-0.08 (-0.10)	-0.31*** (-3.04)	-0.29*** (-3.47)	-0.67 (-1.15)	-0.32 (-0.72)	-0.60*** (-8.67)
Percentage of non-translational-star coll. in an exclusive relationship $_{t-1 \text{ to } t-4}$**	-0.55*** (-22.68)	-0.22*** (-5.46)	-0.57 (-0.71)	-0.20* (-1.66)	-0.45*** (-3.18)	-0.00 (-0.06)	-0.40 (-0.50)	-0.03 (-0.13)
Dummy for biotech firm	-0.15*** (-3.18)	-0.20*** (-5.41)	-0.11 (-0.50)	-0.10 (-1.16)	-0.30*** (-4.83)	-0.32* (-1.72)	-0.24 (-1.31)	-0.35* (-1.88)
Dummy for instrument firm	0.00 (0.02)	-0.05 (-0.88)	-0.02 (-0.02)	-0.01 (-0.15)	-0.06** (-2.51)	0.01 (0.07)	-0.06 (-0.43)	0.09 (0.46)
_cons	0.59*** (70.79)	0.54*** (287.83)	-0.60 (-0.36)	0.28** (2.07)	-0.21 (-1.04)	0.37 (0.79)	-0.29 (-0.32)	0.41 (0.58)