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Auteurs

Karine Revet, Isabel Maria Bodas-Freitas, Barthélemy Chollet, Pablo D'Este

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www.beta-umr7522.fr

@beta_economics

Contact :
jaoulgrammare@beta-cnrs.unistra.fr

Exploring resource seeking in a scientific collaboration network and its effect on scientists' knowledge creation

Karine Revet [a,b,c], Isabel Maria Bodas-Freitas [d], Barthélemy Chollet [d,c], Pablo D'Este [e]

[a] ICN Business School, Nancy, France
[b] Université de Strasbourg, Université de Lorraine, CNRS, BETA, 67000, Strasbourg, France
[c] Université Savoie Mont-Blanc, IREGE, France
[d] Grenoble Ecole de Management, France
[e] INGENIO (CSIC-UPV), Universitat Politècnica de València, Camino de Vera s/n, 46022 Valencia, Spain

Abstract

Scientists display heterogeneous profiles regarding the focus of their knowledge production activities, their collaboration strategies and their outcomes. Despite increasing interests on research collaboration, little is known about how scientists mobilize their research network. In their knowledge creation efforts, scientists collaborate with colleagues from both academia and industry. These collaborations, leading or not to co-authorship, allow scientists to access to a number of research resources. The objective of this study is to explore whether and how knowledge production across the four Stokes' quadrants (different focus on fundamental understandings and on immediate industrial and social application) is associated with specific modes of mobilizing research resources. This study examines empirically the relationship between scientific knowledge production, research resources and collaboration networks, using bibliometric and survey data on 116 scientists active in biotechnology in the Netherlands. Our results suggest that different knowledge creation objectives and outcomes are associated with particular ways of activating the network, and mobilize it to access specific research resources.

Keywords

Knowledge creation – Scientific networks – University-Industry collaboration – Resources – Contributions

JEL codes

M10, O30

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1. Introduction

By collaborating, scientists pool a variety of resources essential to the creation of new knowledge. Enabling a labour division of research activities (Foray & Steinmueller, 2003), "there is something to gain, whether material, intellectual or social" (Melin, 2000, p. 38) from working with scientific colleagues, both academic and industrial (Ankrah & AL-Tabbaa, 2015; Balconi et al., 2004; D'Este et al., 2019; D'Este & Patel, 2007; Haeussler, 2011). Thus, a scientist's productivity may be determined by how they mobilize their relationships (Gonzalez-Brambila et al., 2013; Li et al., 2013; Rotolo & Messeni Petruzzelli, 2013). A recent contribution focusing on scientists involved in simultaneous discoveries argue that the significant higher number of follow up publications of scientists collaborating with industrial colleagues compared to scientists collaborating with academic colleagues only reflect their possibility for focusing only on fundamental understanding rather than also on commercialization activities (Bikard et al., 2018).

However, in addition to formal relationships (i.e. collaborations reflected in co-authorship), informal relationships (i.e. collaborations beyond co-authorship) are also crucial for accessing specific resources such as advice, ideas and fun (Brennecke & Rank, 2016; Chollet & Revet, 2023). In addition, different collaborations may enable the access to different resources, and open different possibilities for labor division. For example, collaborations with industrial colleagues enable access to facilities, equipment and data (Ankrah & AL-Tabbaa, 2015). Thus, depending on their research objectives, researchers can develop and mobilise specific relationships in their research network. However, despite recent research on the types of resources scientists can mobilize (Ankrah & AL-Tabbaa, 2015), the role of informal relationships (Brennecke & Rank, 2016; Chollet & Revet, 2023), the consequences of academic labour division (Teodoridis et al., 2019; Walsh et al., 2019) or its many forms (Haeussler & Sauermann, 2020), we still know little about how scientists' collaboration strategies relate to their specific research interests and motivations. Getting a better understanding of specific network relationships that support scientists' access to complementary resources may permit to identify the bottlenecks of different knowledge production activities and the main channels for scientists to improve their productivity. Therefore, it constitutes the objective of this study to examine the network mobilization strategies of scientists with different research motivations and focus.

Building on network research, we develop a theoretical framework that proposes that the forms and functionality of relationships used by scientists differ according to their contribution profile. According to the quadrants of the Stokes model, scientists differ in terms of the industrial and social impact of their research, on the one hand, and in terms of the extent to which it advances fundamental knowledge (Stokes, 2011). Given these differences, scientists may develop not only different networks but may also rely on different relationships to access complementary resources.

Identifying the network peculiarities across the four Stokes quadrants entails depicting the forms of network mobilization strategy of scientists with different research profiles. Consequently, it is important to trace the complementary resources activated by the scientists (Georghiou, 1998), and the form in which the relationship was mobilized (formally, i.e. as part of a co-authorship relationship or informally, and therefore not captured by the study of co-authorship networks) (Paul-Hus et al., 2017; Rotolo et al., 2022; Tian et al., 2021). For that purpose, we collected primary and bibliometric data on 116 scientists active in biotechnology in the Netherlands. Our results suggest that different knowledge creation profiles across Stockes' model are associated with particular ways of mobilizing the network to access specific research resources.

This study contributes to the economics of science, which has extensively documented academics motivations, practices and productivity, by bringing insights from an ego-centric network approach (McFadyen et al., 2009). We provide evidence that scientists with different profiles do not only differ in their research focus and results. Due to their different knowledge creation objectives, they differ in the way they mobilize their collaboration networks, in terms of size and composition of the network, as well as the type of resources sought.

The paper is organized as follows. Section 2 reviews the literature on scientific collaboration by focusing on resources sought in the network and exchanged between scientists. Section 3 describes the context of our empirical study and the data collection approach. Section 4 presents the results of our statistical analyses. Section 5 synthesizes and discusses the main findings of our study.

2. Literature review

2.1. Scientists' research motivation and profiles

Scientists, in their knowledge creation activities, may pursue several objectives, mixing academic knowledge advancement on the one hand, and practical use for the benefit of society on the other. The former can be referred to as basic research. It is characterized by its orientation based on curiosity and the will to develop new knowledge for its own sake (Salter & Martin, 2001), and its objective of generalization (Pavitt, 1991). The latter is labelled as applied science and is inspired by considerations of use and application in industry, relating to technology, techniques, methods and design (Balconi & Laboranti, 2006).

The spectrum of basic/applied research is broadly adopted to understand scientists' research orientations (Berbegal-Mirabent & Sabate, 2015; Fan et al., 2021; Hameri, 1996; van Raan & van Leeuwen, 2002). To take into account the extent to which individual scientists can combine these two aspects in their research, Stokes (2011) suggests a two-dimensional classification that describes four quadrants - corresponding to four research profiles - in which scientists can be classified (see Figure 1). The first dimension takes into account scientific interest and the quest for fundamental understanding. In this dimension, the extent to which the scientist's work seeks relevance for generalized knowledge is taken into account. The second dimension accounts for technical interest and consideration of use. This dimension captures the extent to which the scientist's work seeks relevance for immediate applications.

Edison scientists are described as scientists interested only in pure applied research, working to develop knowledge and propose inventions that meet the needs of individuals and society (Baba et al., 2009). *Bohr scientists*, also referred to as Star scientists, are defined as scientists with a strong interest in science and pure basic research (Colen et al., 2022; Sauermann & Stephan, 2013). They are individuals who are "oriented to the pursuit of knowledge and understanding for its own sake through scientific discovery, having little interest in the potential uses of the research findings for the real world" (Baba et al., 2009, p. 757). Finally, *Pasteur scientists* are individuals who bridge the gap between science and technology by being heavily involved in both the development of high quality theoretical knowledge and the development of its application in the real world (Baba et al., 2009). This latter profile can be associated with the concept of the academic-inventor, scientists who are highly successful both in publishing academic papers (reflecting their commitment to fundamental understanding) and in patenting (invention activity associated with consideration of use) (Fabrizio & Di Minin, 2008; Franzoni, 2009; Subramanian et al., 2013; Van Looy et al., 2006).

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Several studies have investigated scientists' profiles (e.g. Amara et al., 2019; Baba et al., 2009; Siegel, 2022; Subramanian et al., 2013; Tushman & O'Reilly, 2007). They focused on understanding the specificities of scientists' in terms of knowledge production. Individual scientists, depending on their profile, are described as performing differently in their knowledge creation activities (Shichijo et al., 2015). On the one hand, scientists oriented towards fundamental understanding are more likely to publish a greater number of scientific papers, and generate more impactful papers for the scientific community (Baba et al., 2009; Colen et al., 2022; Subramanian et al., 2013). In this approach of the productivity of scientists, many researches have focused on star scientists (Bohr profile) due to their outstanding publication performance (e.g. Calderini et al., 2007; Colen et al., 2022; Liu et al., 2018; Mohnen, 2021; Oettl, 2012). On the other hand, scientists who are more use-oriented are particularly invested in invention activities and consequently demonstrate above average patent records (Subramanian et al., 2013). Thus, depending on their profile, the knowledge creation of scientists could be assessed by two types of outputs, publications and patents, in which they perform differently. One should take into consideration that this is a general trend, and therefore that for example scientists with a weak orientation towards the application of knowledge created to contribute to industry and society may nevertheless have some [2]patenting activity (Zucker et al., 1998).

2.2. Role of scientists' profile in seeking resource in academic or industrial networks

Scientists' research orientations, as reflected in Stokes' (2011) four quadrants, are likely to affect the nature of the collaborators in the research network of individual scientists, with the distinction being made between networks including academic versus industry scientists (Haeussler, 2011; Sauermann & Stephan, 2013; Subramanian et al., 2013).

Collaborations between industrial and academic scientists are known to have an impact on their knowledge creation. Previous research suggests that academic scientists involved in collaborations with industry may experience lower publication rates due to the pressure from industry to protect intellectual property through patents or secrecy (Bikard et al., 2018). Colen et al. (2022) argue that the strong commitment of Bohr scientists to scientific discovery and open science may hamper any commitment to extensive collaborations with industry . Pasteur scientists, on the contrary, can benefit from a more optimal division of labor by having collaborators from both industry (focus on commercial uses) and academia (focus on scientific discoveries) (Bikard et al., 2018). Patenting and publishing activities can be complementary, up to a certain threshold beyond which the two knowledge creation activities become substitutes

(Crespi et al., 2011). Scientists fitting into the Pasteur and Edison profiles can be described as 'bridging scientists' spanning academic and industrial domains (Subramanian et al., 2013). Science-technology interactions among scientists from these two worlds are also known to be highly skewed, involving only a few scientists (from the Pasteur profile), that are engaged in a large number of interactions (Agrawal & Henderson, 2002; Balconi et al., 2004). While, as previously discussed, scientists of various profiles engage differently in the creation of knowledge outputs, it is important to stress that the choice to engage in publication or patent production does not in itself constitute an interaction with industry, but rather a move towards proprietary knowledge and commercialization activities (D'Este & Patel, 2007).

Beyond scientists' research aspirations, the content of the exchanges that may exist between academic and industrial scientists can be the source of different patterns of collaboration. Research has a long history of identifying the different channels of collaboration between scientists in academia and industry. These collaborations are varied and can take place through contracted research activities, employment of academic scientists by industry, entrepreneurial activities such as joint ventures and spin-offs, consultancy work, consortia, networks and alliances (Ankrah & AL-Tabbaa, 2015; Bekkers & Bodas Freitas, 2008; D'Este et al., 2019; D'Este & Patel, 2007; Perkmann et al., 2011). Furthermore, the literature tends to argue that the relationship between academia and industry is increasingly close, and that the traditional boundary between the two is becoming blurred (Subramanian et al., 2013): the academic and industrial domains are no longer "separate worlds" (Haeussler, 2011, p. 108).

Therefore, it seems important to better understand how these two worlds are related and what differences between them persist. First, these partnerships and collaborations between academic and industry scientists are recognized as a way for companies to access basic research as well as to develop applied research (Balconi & Laboranti, 2006; Cassiman et al., 2018). Therefore, collaborations between scientists in academia and industry are desirable for firms as it allows them to nurture their research activities, and to benefit from the inputs of scientists conducting basic research, mainly located in academia (Agarwal & Ohyama, 2013). Second, academia and industry provide access to different but potentially complementary physical capital (Agarwal & Ohyama, 2013). Indeed, tangible resources and reusable assets such as equipment and machines, technologies and raw materials, as well as sources of funding, accessible in academia or in industry, may differ. Thus scientists from different profiles, depending on their needs for such resources, may benefit differently from their research network in the two worlds. Collaborations between scientists from academia and industry is described as a way to gain access to complementary assets and to overcome the limitation of one domain or the other (Baba et al., 2009). These elements suggest that scientists with different research profiles collaborate differently with industry, both in the extent to which they mobilize their industrial research network, and in the resources they seek in that network.

2.3. Role of scientists' profile in seeking resource in formal or informal networks

Every individual scientist, in their knowledge creation activities, is led to develop a research network with collaborations of different natures, rather formal or informal, both of which are widely recognized in the sciences as having different contributions and thus allowing access to various resources. On the one hand, formal relationships are clearly visible and identifiable relationships, leading to co-authorship or co-invention (depending on the type of knowledge output considered) (Apa et al., 2021). These relationships are guided by identified contribution rules, some of them common to all scientific work and others depending on the scientific discipline. These rules generally imply that each collaborator listed on the knowledge output has had a significant contribution in this knowledge creation work, according to the modalities of division of scientific work (Haeussler & Sauermann, 2020; Sauermann & Haeussler, 2017). On the other hand, other forms of collaboration remain "invisible" in the sense that they do not materialize directly through knowledge outputs (Apa et al., 2021). However, these more informal collaborations are also a key means used by individual scientists to access information, knowledge, and to receive advice or recommendations useful to their knowledge creation work (Birnholtz, 2006; Chollet & Revet, 2023; Haeussler & Sauermann, 2013; Paul-Hus et al., 2017; Tian et al., 2021). These invisible relationships may also involve participating in the division of scientific labor but on tasks or contributions that are generally accepted as not significant enough to lead to co-authoring or co-patenting.

Scientists are influenced by their peers through social comparison (Tartari et al., 2014). This social influence has direct impact on scientists' knowledge creation. For example, coauthoring with a star scientist (Bohr profile) has a positive impact on their peers' research performance in term of impact and citations (Betancourt et al., 2023). Scientists performing basic research also more generally affect positively the productivity of their colleagues, even when they do not co-author papers (Yadav et al., 2023). Collaboration exists beyond the co-authorship relationship. However, this questions how formal and informal relationships differ in what they provide to a focal scientist.

This social influence among scientists is not limited to scientists' knowledge creation performance, and may affect their exchanges and interactions with both academia and industry (Tartari et al., 2014). Indeed, knowledge creation and the associated exchanges with industry are rooted in social exchange phenomena involving informal exchanges (Ankrah & AL-Tabbaa, 2015). Although most studies focus on formal collaborations, informal forms have be shown to be more beneficial to the innovation performance of companies (Apa et al., 2021; Perkmann et al., 2013). Thus, if informal collaborations are beneficial for companies and act as a channel for knowledge transfer, it seems interesting to question to what extent they can also be beneficial for scientists and be a vehicle for the exchange of other types of resources than knowledge. Additionally, formal collaboration channels between academic and industry scientist appear to play only a limited role in knowledge resources exchanges between the two worlds (Baba et al., 2009), suggesting that informal collaborations could alternatively be important such exchanges. The resources contributed by partners in the context of academia-industry collaborations are central to addressing critical resource needs such as funding, equipment and skilled staff (Rybnicek & Königsgruber, 2019). This sharing of resources from industry through informal relationships is also a way of influencing the research efforts of scientists, without engaging in formal collaborations leading for example to co-authoring publications (Rotolo et al., 2022).

These elements suggest that the resources sought do not simply differ according to the nature of the network, academic or industrial (as previously established), but also according to the form of collaboration, formal or informal. Scientists from different research profiles, depending on the needs associated with the type of research conducted, may therefore benefit differently from formal or informal collaborations in their seeking of different resources.

3. Methodology

To capture the way scientists activate their networks to access different types of resources, and to understand the effects of these strategies on their knowledge creation performance, we sequentially collected data from two complementary sources. First, we collected bibliometric data on an identified population of biotechnology scientists in the Netherlands, and then we integrated this information into a questionnaire sent by e-mail to them.

3.1. Setting

Our empirical study focuses specifically on the biology and biotechnology sector. It is widely accepted that there are differences between sectors and disciplines in the way they approach knowledge production, collaborations and relationships with industry (Bekkers & Bodas Freitas, 2008). The biology and biotechnology sector is recognized as a high-impact, high-stakes sector in which industry and the public sector collaborate closely (Powell et al., 1996; Soh & Subramanian, 2014). It is a sector that, due to its specificities, has been the focus of much research attention (e.g., Colen et al., 2022; Franzoni, 2009; Gittelman & Kogut, 2003; Lim, 2004; Perkmann et al., 2011; Subramanian et al., 2013).

Because there are differences in the academic system, in funding, support and incentive policies between countries, we also decide to restrict our study to a specific national context, that of the Netherlands. The Dutch academic system is based on research and technical universities. While research universities are focused on academic activities, technical universities are known to focus more on practical aspects and applications.

Four interviews with key informants in the Netherlands (professor emeritus in biology, director of a research center in biology and biotechnology, professor and business development director in a research center in biology, coordinator of intellectual property at the university) inform us about the specificities of the field to be taken into account in our investigations.

The choices on the research setting lead us to identify an initial list of 820 scientists with an affiliation to a Dutch university (either research or technical university) in a biology and biotechnology research laboratory. We supplement this initial list with a snowball method by including the Dutch co-authors of these individuals, who may be affiliated with other research laboratories, private organizations or industrial companies. Indeed, as the field of biotechnology is multidisciplinary, it is appropriate to integrate those scientists who are affiliated to other research laboratories, but who also work on these themes (in collaboration with scientists specialised in biotechnology). This approach allows us to build a list of 1776 individuals, of which 1511 individuals for whom we are able to manually retrieve a valid email address.

3.2. Data collection

3.2.1. Bibliometric data

Regarding the bibliometric data collection, we manually collected data on publications (from Web of Science and Google Scholar) and patents (see e.g., Bikard et al., 2018; Bikard & Marx, 2019; Bourelos et al., 2017; Breschi et al., 2005; Meyer, 2006) for all 1511 identified scientists. These data provide us with information on the knowledge creation performance of each scientist with a valid email address. These bibliometric data also allow us to identify the list of formal collaborators of each scientist.

3.2.2. Survey data

In a second step, we integrate the bibliometric data into a questionnaire. The questionnaire aims to obtain information about the colleagues with whom the scientist collaborates, the nature of their relationship, and the resources sought from each colleague.

Two of the interviewees provided detailed qualitative feedback on the questionnaire items, based on their expertise in the field of biotechnology and the specificities of the Netherlands. Additionally, pre-test of the questionnaire was conducted with 6 biotechnology scientists, and feedback from them regarding their understanding of the questions, the language and technical words and the collaborations practices was collected through telephone interviews.

We administered the final version of the questionnaire to our study population through an email invitation. We obtained 117 questionnaires, corresponding to a final response rate of 7.7%. Due to missing data on our main collaboration variables in one questionnaire, 116 were used for the analyses.

3.3. Variables

The operational definitions of all the variables are presented in detail below and in Appendix A.

3.3.1. Dependent variables

Studies operating Stokes's quadrant model of scientific research are rare (Amara et al., 2019), and the approaches heterogeneous. Several authors suggest to operationalize the two dimensions of the model through the knowledge outputs of scientists (Baba et al., 2009; Gittelman & Kogut, 2003; Martínez et al., 2013; Subramanian et al., 2013). It is thus proposed that a higher number of academic publications and high citations of these publications capture the dimension of fundamental understanding, while the presence of patenting activity accounts for the consideration of use. However, this approach has its limitations, related to the fact that basic research oriented scientists can also report patents (Zucker et al., 1998) and that patents are not the only way to consider the use of knowledge created in society (Amara et al., 2019). An alternative may be to consider the research motivations of scientists, taking into account both the intellectual challenge and the contribution to society (Amara et al., 2019).

In this study, we adopt a mixed approach of these two methods. On the one hand, concerning the first dimension of the model on the quest for fundamental understanding, the method based on motivations does not appear to be appropriate for differentiating the profiles of scientists. Indeed, the answers obtained on the motivation to advance knowledge and intellectual curiosity show that this criterion is central for a large majority of the respondents (79.3% answered "very important"). Therefore, the knowledge output approach seems to be the most appropriate to differentiate the respondents. To operationalize this dimension, we consider that a scientist has a high quest for fundamental understanding if they have an above average number of citations per published academic article or if they have published in journals recognized for their key role in the advancement of scientific knowledge (Nature or Science).

On the other hand, regarding the second dimension of the model on consideration of use, and to avoid the limitations identified with regard to the use of patents to capture this dimension, we focus on the scientist's motivation to make a contribution to society (43.1%

answered "very important"). This is consistent with the information collected during the qualitative interviews with key informants who indicated that while patenting was an option, some scientists might not go through this option (expensive and not always advantageous for scientists due to specific university policies), and might thus for example decide instead to work directly with companies or to create their own spin-off. This can be observed for our respondents since one third of the scientists declaring a very high motivation to contribute to society do not have any patenting activity.

3.3.2. Network variables

To be consistent with our theoretical distinction between academic and industrial networks, and formal and informal networks, the questionnaire includes four questions to capture these different collaborations. More precisely, the questionnaire is based on two forms of network question. First, integrating the bibliometric data, we list all co-authors over the last 5 years of each individual scientist[1]. We then ask them to choose from this list of formal collaborators up to 5 names of colleagues with whom they have collaborated closely.

Second, we use a name generator (Knoke & Yang, 2008) to capture the informal collaboration network of each scientist. We ask them to name up to 5 colleagues with whom they have collaborated closely in the last 5 years, but who are not co-authors in this period.

Finally, for each of these two types of question, we distinguish between scientists colleagues having their main affiliation in academia or industry. This approach allows each individual scientist to identify up to 20 colleagues in their network.

To study the collaboration of scientists and to see to what extent each individual scientist relies on different networks, we use several variables. To capture the extent of the network of each individual scientist, we use a binary variable *Large Network* that indicates scientists with an above average number of contacts (one standard deviation above the average of all respondents). Then, to capture the nature of this overall network, we rely on two other variables: *Informality (academia)* represents the share of academic informal contacts among all listed colleagues, and *Industrial* measures the part of colleagues in industry in the whole network.

In a second phase of the survey, we use name interpreters to collect information or each colleague identified the individual scientists. This information includes socio-demographic data (gender, age), affiliation (at the same institution as the scientist concerned, at another institution in the Netherlands, or outside the Netherlands), the nature of the relationship (PhD student or

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[1] In cases where the number of collaborators over the last 5 years is greater than 100, the most frequent co-authors were listed.

supervisor) and the strength of the relationship (duration of the relationship, ongoing collaboration).

3.3.3. Resources variables

In addition to the name interpreters, we further asked respondents to consider the last collaboration they had with each identified colleague, and to identify the contributions and resources provided by that colleague. Respondents were then given a list of 7 resources to choose from, including *Knowledge*, *Idea*, *Skill*, *Equipment*, *Data*, *Funding*, and *Fun (*see Appendix B). Respondents were given the option, for each colleague, to indicate one, several, or no resources. These data were then aggregated to consider the presence of each resource according to the type of network mobilized (academic or industrial, formal or informal), taking into account the proportion of contacts from the same type of network that were used to seek this resource.

In addition to these variables, we also take into account the multiplexity in the relationship with colleagues, in other words the extent to which respondents mobilize the same colleague to access several resources. The *Multiplexity* variable therefore indicates the average number of resources provided per colleague in the individual scientist' network. This variable is computed by measuring for each contact identified by the scientist, the number of resources contributed by that contact (between 0 and 7), and then averaging this value over all contacts in the individual scientist's network.

Finally, the *Scarcity* variable counts the number of resources for which the respondent mobilizes only one person in their network to access them. The objective of this variable is to account for the extent to which each scientist has a complementarity strategy by mobilizing several colleagues to access the same resource.

3.3.4. Control variables

To take into account other individual aspects that may interact with the elements analyzed in this study, we also consider some control variables at the individual level. First, we include variables to capture the socio-demographic characteristics of the scientists, namely son-in-law (if the scientist is a *Male*), and academic status (binary variable at 1 if the scientist has a status of *Professor*, full professor, emeritus professor; 0 otherwise). Then, to take into account the specificities of the Dutch academic system, we also control for the scientist's main university affiliation (dummy variable at 1 if affiliated in a *Technical university*, 0 otherwise). Finally, we capture the fact that respondents have completed their *PhD abroad* or a *Post-doc abroad* through two binary variables.

3.4. Estimation approach

The aim of our analyses is to examine the differences between scientists of different profiles, both in the way they mobilize their network and in the way they search for resources in the network. To study the characteristics of the different profiles of scientists, we first present a set of descriptive statistics and bivariate analyses.

In a second step, we perform regressions that aim to capture the factors that explain why scientists belong to different profiles. In accordance with the nature of our dependent variable based on the 4 scientists' profiled derived from Stokes' quadrant model of scientific research, we use the multinomial logit estimation method, as it is the most appropriate model for multi-value unordered dependent variables. The tinkering assignment (with low consideration of use and low quest for fundamental understanding) was considered as the reference assignment.

4. Results

Table I provides the descriptive statistics of the main variables used in the regression analyses of this study. Our sample consists mainly of men (n=12, 87.93%), working in a research university (n=81, 69.83%). Most of them obtained their Ph.D. in the Netherlands (n=89, 76.72%) on average 23 years ago (s.d. = 12.86). A majority of respondents have the status of professor (professor, full professor or emeritus professor, n=50, 43.10%), the other respondents being assistant professor (n=24, 20.69%), associate professor (n=17, 14.66%) or researcher (n=17, 14.66%). 8 respondents have a position outside academia (6.90%).

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While no correlation is high enough to suspect multicollinearity, some expected relationships become apparent. Logically, respondents who obtained their doctorate longer ago (career duration) are more likely to have the status of professor, full professor or emeritus professor. Having a more developed industrial network implies having a larger whole network (network size). As might be expected, multiplexity is correlated with all resources measures (knowledge, idea, skill, equipment, data, funding and fun).

4.1. Scientists' profiles and bivariate analysis

Figure 2 presents the distribution of scientists of our sample across the four quadrants of Stokes' model of scientific research. The distribution shows that a majority of scientists fall into the tinkering category (32.76%) while the rarest scientist profile is the Pasteur profile (18.97%). Both the Bohr and Edison profiles account for 24.14% of the scientists in our sample. This fairly balanced distribution allows us to compare the characteristics of scientists belonging to each profile.

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Table II provides a picture of the scientists in our sample by comparing the four quadrants (profiles) to which they belong. Regarding the characteristics of individual scientists, these results show that belonging to different profiles does not depend on the scientist's gender, career duration or affiliation. While having the status of professor is significantly more frequent for researchers in the Pasteur profile compared to the Edison profile (t-test(114)=2.44, $p<0.1$), the difference between the other profiles is not significant. Having done a PhD abroad does not influence the fact that a scientist belongs to one profile rather than another. However, doing a post-doctorate abroad is significantly more important for scientists with a high quest for fundamental understanding (namely Bohr and Pasteur profiles). Doing a post-doc abroad is a prestigious opportunity that is widely recognized as beneficial for an academic career and is generally followed by the most motivated PhD students in terms of developing expertise and in-depth knowledge.

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In line with what has been reported in the literature (Subramanian et al., 2013), scientists with a high consideration of use (Edison or Pasteur profile) show the highest patenting activity (t-test(114)= 9.59, $p<0.01$). Examining the connections with industry, we show that scientists with high consideration of use are significantly more involved in spin-off or start-up development than scientists with low consideration of use (t-test(114)= 4.95, $p<0.05$), and mobilize more funding from industry sources (t-test(114)= 4.84, $p<0.05$). However, these differences between scientists with research seeking relevance for immediate application to a greater or lesser extent are not significant with regard to having a part-time position in industry or using predominantly industrial knowledge. This may reflect specificities in the context under study.

When looking at the research networks of scientists, we observe that scientists with various profiles differ in several aspects. Pasteur scientists have the largest whole network, significantly larger than Bohr scientists (t-test(114)= 2.63, $p<0.05$). While the size of the academic network of all scientists is similar, Bohr scientists rely significantly less on contacts from industry compared to scientists with a strong consideration of use (Edison, t-test(114)= 3.16, $p<0.05$; and Pasteur, t-test(114)= 3.78, $p<0.01$). In addition, scientists with a higher consideration of use have a significantly larger formal network (t-test(114)= 6.76, $p<0.05$). However, the use of the informal network does not differ across scientists' profiles.

With respect to the characteristics of the networks mobilized by scientists, these also show variations depending on the profile. Scientists with a research strategy oriented only towards basic research (Bohr) or applied research (Edison) mobilize a more local network within their university of affiliation (t-test(114)= 4.89, $p<0.05$). Moreover, scientists with a high quest for fundamental understanding develop a more international network (t-test(114)= 6.67, $p<0.05$). Edison scientists collaborate most extensively with their former thesis supervisor(s), and on the contrary work little with Ph.D. students. No significant differences were found in the duration of the relationships maintained by the scientists with their network according to their profile.

Finally, looking at the resources sought by scientists in their research network, we find several interesting results. First, knowledge and ideas, central to all research work, are the resources most mobilized by scientists, regardless of profile. Second, equipment and data are also sought by all scientists in similar ways. Third, we observe that scientists oriented towards applied research (Edison profile) rely less on their network to access skills, compared to other scientists ($F(3,112)= 3.23$, $p<0.05$). Fourth, we find that scientists strongly committed to contributing to society (Edison and Pasteur profiles) rely more on their research network to seek funding (t-test(114)= 5.40, $p<0.05$). Fifth, scientists oriented towards fundamental understanding (Bohr and Pasteur profiles) are more likely to look for colleagues with whom they enjoy working, who bring fun and motivation (t-test(114)= 4.86, $p<0.05$).

4.2. Regression results

For our regression analyses, we run two main multinomial logit estimation models. Both models include control variables on the individual characteristics of the respondents, as well as variables characterizing the network of each respondent, both in terms of size, informality, and industry linkage. The first model, whose results are presented in Table III, tests more specifically the effect of multiplexity and scarcity of resources; while the second model (see Table IV) tests the effect of each of the seven resources to which collaborators in the research network can contribute.

--------------------------- INSERT TABLE III AND IV HERE ---------------------------

The results of both models suggest that scientists with different profiles differ significantly in several individual characteristics. Scientists with a high quest for fundamental understanding (Bohr and Pasteur profiles) do more post-doctoral work abroad. Scientists developing pure basic research (Bohr profile) or user-inspired research (Pasteur profile) are more likely to have professor status compared to those developing pure applied research (Edison profile). We also find significant differences in the networks of the scientists of the different profiles, notably concerning the Bohr scientists who rely more on their informal network, and significantly less on collaborators from industry.

Regarding the mobilization of resources in the research network, it appears that the four profiles of scientists do not differ significantly either in the multiplexity in the network or in the scarcity of resources (see Table III). However, when we study in detail how scientists from different profiles seek different types of resources in their research network (see Table IV), we find significant differences. Scientists with a Bohr profile rely less on their network to access knowledge resources, but more to access fun resources compared to scientists with other profiles. They also rely less on their collaboration network to access equipment, compared to other researchers with a high quest for fundamental understanding (Pasteur profile). In addition, scientists with a low consideration of use (Bohr and Tinkering profiles) mobilize their network more to access expertise compared to scientists doing pure applied research (Edison profile). In contrast, scientists with a high use consideration (Pasteur and Edison profiles) use their network more to access funding compared to scientists doing pure basic research (Bohr).

5. Discussion and conclusion

Scientists pursue a variety of goals. Some seek to advance knowledge for the sake of knowledge while others preferably work on its applications (Stokes, 2011). Similarly, scientists vary in the type of impact they want to make (Cohen et al., 2020). These differences in contribution profiles must be accounted for when studying the conditions to which scientists can perform at their best. In this paper, we suggest that differences in contribution profiles imply differences in terms of network mobilization. We surveyed a sample of researchers in biotechnologies, in the Netherlands, about the types of resources they seek from their collaborators in the broad sense – not just the people appearing formally as their co-authors. Our results show that the types of relationships and resources sought from network mobilization vary across Stokes's quadrant.

Consistent with prior findings (e.g., Shichijo et al., 2015) and quite intuitively, Edison and Pasteur profiles tend to have more collaborators from the industry than Bohr and Tinker profiles. Another set of findings seems to reflect the specific division of labor required for each profile to conduct research successfully. "Funding" is a resource sought for significantly more by Edison and Pasteur profiles, consistent with their focus on more immediate impact, which often entails a strict attachment of a project to a specific funding, often commissioned by key stakeholders. Also, Bohr profiles seek from their collaboration more skills in specific experimental or analytical techniques and less pure knowledge of a research topic, especially relative to Edison profiles. This difference probably reflects indirectly the resources these profiles already possess as human capital and thus what resources are complementary to theirs (Edison profiles holding the skills and Bohr profiles, knowledge).

Perhaps less intuitive is the finding that the level of informality (the proportion of people among academic contacts cited as collaborators that are not co-authors) is significantly higher among Bohr profiles (i.e., scientists with a strong impact in the publication world and a low focus on impacting society). By definition, Bohr profiles work on less structured problems or objectives than Edison and Pasteur scientists, and spend most of their time exploring "the unknown". This higher open-endedness has two implications for collaboration work. First, an important amount of energy must be assigned to idea development, testing and refinement, to define a project. This is where informal interactions are known to be essential, people consulting with colleagues to obtain feedback on their ideas and "mutual stimulation" to develop further an ill-defined idea (Laudel, 2002). Second, the set of resources they need is necessarily less definable ex-ante than for projects where the problem is highly structured. Thus, Bohr profiles need to maintain a pool of potential contributors who may or may not become co-author at some point in a given project, depending on what resource turns out to be needed. This could also explain why, in our findings, the resource "fun" is more cited among Bohr profiles when qualifying resources brought by collaborators. In situations where the actual set of tasks is uncertain and open ex-ante, relying on strong and trusted relationships is a good way to guarantee the minimal level of common understanding and mutual commitment to allow adaptation along the way (McFadyen et al., 2009).

The contribution of the paper is three-fold. First, the literature examining what resource scientists seek from collaborators is still incomplete. Some research consists in surveying scientists about their motives for collaborating with someone, in search of how these patterns vary according to individual or contextual characteristics (Bozeman & Corley, 2004; Bozeman & Gaughan, 2011; Muriithi et al., 2018). This paper extends this line of work by suggesting that resources sought for by scientists also depend on their orientation in terms of consideration for use and focus on fundamental understanding (Stokes, 2011). Second, we contribute to the many reflections on how scientists engage with industry and society at large (Agarwal & Ohyama, 2013; Sauermann & Stephan, 2013; Tijssen, 2018). While prior work has studied how positions on the quadrant goes with differences in production outputs (e.g., (Shichijo et al., 2015) or impact on organizational performance (e.g., (Baba et al., 2009; Perkmann et al., 2021; Subramanian et al., 2013), research examining networking behaviors are rare and focus only holistic constructs such as the proportion of industry contacts (e.g., Ng et al. 2015, cited in Tijssen, 2018). Delineating specifically the resources sought through these relationships helps better understanding the division of labor that sustains each type of research effort. Third, we contribute to the growing efforts to take into account a wider range of collaborations, not limited to coauthorship but including traditionally invisible informal collaborations (e.g., Apa et al., 2021). In line with these efforts, this work provides further reflection on the different contributions of formal and informal relationships, involving different contributions.

However, this paper also comprises limitations that further work need to address. First, the field of biotechnologies has peculiarities that limit the generalizability of our findings. Innovations in biotechnologies are heavily “science-based”, in the sense that it relies heavily on research produced by universities and public research agencies (Coriat et al., 2003). Accordingly, university/industry linkages are particularly widespread and essential to the creation of commercializable products or services (George et al., 2002; Kolympiris et al., 2015; Stuart et al., 2007). Research in other fields might show different patterns of network mobilization. Moreover, although relying on surveys allows better capturing the content of collaboration relationships and underlying motives, beyond what bibliometric measures can deliver, it also entails limitations. When surveyed on their network, respondents rely on their memory and thus can be biased (Shea et al., 2015). Also, due to the challenge of maintaining a reasonable survey length, our questions pertaining resources brought by collaborators where asked for the latest collaboration event. However, collaboration roles may rotate from one project to the other, leading some collaborators to bring different resources according to the project.

References

Agarwal, R., & Ohyama, A. (2013). Industry or Academia, Basic or Applied? Career Choices and Earnings Trajectories of Scientists. *Management Science, 59*(4), 950-970. https://doi.org/10.1287/mnsc.1120.1582

Agrawal, A., & Henderson, R. (2002). Putting Patents in Context : Exploring Knowledge Transfer from MIT. *Management Science*, *48*(1), 44-60.

Amara, N., Olmos-Peñuela, J., & Fernández-de-Lucio, I. (2019). Overcoming the "lost before translation" problem : An exploratory study. *Research Policy*, *48*(1), 22-36. https://doi.org/10.1016/j.respol.2018.07.016

Ankrah, S., & AL-Tabbaa, O. (2015). Universities–industry collaboration : A systematic review. *Scandinavian Journal of Management*, *31*(3), 387-408. https://doi.org/10.1016/j.scaman.2015.02.003

Apa, R., De Marchi, V., Grandinetti, R., & Sedita, S. R. (2021). University-SME collaboration and innovation performance : The role of informal relationships and absorptive capacity. *The Journal of Technology Transfer*, *46*(4), 961-988. https://doi.org/10.1007/s10961-020-09802-9

Baba, Y., Shichijo, N., & Sedita, S. R. (2009). How do collaborations with universities affect firms' innovative performance? The role of "Pasteur scientists" in the advanced materials field. *Research Policy*, *38*(5), 756-764. https://doi.org/10.1016/j.respol.2009.01.006

Balconi, M., Breschi, S., & Lissoni, F. (2004). Networks of inventors and the role of academia : An exploration of Italian patent data. *Research Policy*, *33*(1), 127-145. https://doi.org/10.1016/S0048-7333(03)00108-2

Balconi, M., & Laboranti, A. (2006). University–industry interactions in applied research : The case of microelectronics. *Research Policy*, *35*(10), 1616-1630. https://doi.org/10.1016/j.respol.2006.09.018

Bekkers, R., & Bodas Freitas, I. M. (2008). Analysing knowledge transfer channels between universities and industry : To what degree do sectors also matter? *Research Policy*, *37*(10), 1837-1853. https://doi.org/10.1016/j.respol.2008.07.007

Berbegal-Mirabent, J., & Sabate, F. (2015). Balancing basic and applied research outputs : A study of the trade-offs between publishing and patenting. *Technology Analysis & Strategic Management*, *27*(10), 1143-1158. https://doi.org/10.1080/09537325.2015.1060313

Betancourt, N., Jochem, T., & Otner, S. M. G. (2023). Standing on the shoulders of giants : How star scientists influence their coauthors. *Research Policy*, *52*(1), 104624. https://doi.org/10.1016/j.respol.2022.104624

Bikard, M., & Marx, M. (2019). Bridging Academia and Industry : How Geographic Hubs Connect University Science and Corporate Technology. *Management Science*. https://doi.org/10.1287/mnsc.2019.3385

Bikard, M., Vakili, K., & Teodoridis, F. (2018). When Collaboration Bridges Institutions : The Impact of University–Industry Collaboration on Academic Productivity. *Organization Science*. https://doi.org/10.1287/orsc.2018.1235

Birnholtz, J. P. (2006). What does it mean to be an author? The intersection of credit, contribution, and collaboration in science. *Journal of the American Society for Information Science and Technology*, *57*(13), 1758-1770. https://doi.org/10.1002/asi.20380

Bourelos, E., Beyhan, B., & McKelvey, M. (2017). Is the prominent scientist the one who becomes an inventor? A matching of Swedish academic pairs in nanoscience to examine

the effect of publishing on patenting. *Research Evaluation*, *26*(2), 144-156. https://doi.org/10.1093/reseval/rvx004
Bozeman, B., & Corley, E. (2004). Scientists' collaboration strategies : Implications for scientific and technical human capital. *Research Policy*, *33*(4), 599-616.
Bozeman, B., & Gaughan, M. (2011). How do men and women differ in research collaborations? An analysis of the collaborative motives and strategies of academic researchers. *Research Policy*, *40*(10), 1393-1402.
Brennecke, J., & Rank, O. N. (2016). The Firm's Knowledge Network and the Transfer of Advice among Corporate Inventors. *Academy of Management Proceedings*, *2016*(1), 11787. https://doi.org/10.5465/ambpp.2016.125
Breschi, S., Lissoni, F., & Montobbio, F. (2005). From Publishing to Patenting : Do Productive Scientists Turn into Academi Inventors ? *Revue d'économie Industrielle*, *110*(1), 75-102. https://doi.org/10.3406/rei.2005.3073
Calderini, M., Franzoni, C., & Vezzulli, A. (2007). If star scientists do not patent : The effect of productivity, basicness and impact on the decision to patent in the academic world. *Research Policy*, *36*(3), 303-319. https://doi.org/10.1016/j.respol.2006.11.007
Cassiman, B., Veugelers, R., & Arts, S. (2018). Mind the gap : Capturing value from basic research through combining mobile inventors and partnerships. *Research Policy*, *47*(9), 1811-1824. https://doi.org/10.1016/j.respol.2018.06.015
Chollet, B., & Revet, K. (2023). Digging deep or scratching the surface? Contingent innovation outcomes of seeking advice from geographically distant ties. *Technological Forecasting and Social Change*, *189*, 122367. https://doi.org/10.1016/j.techfore.2023.122367
Cohen, W. M., Sauermann, H., & Stephan, P. (2020). Not in the job description : The commercial activities of academic scientists and engineers. *Management Science*, *66*(9), 4108-4117.
Colen, L., Belderbos, R., Kelchtermans, S., & Leten, B. (2022). Reaching for the stars : When does basic research collaboration between firms and academic star scientists benefit firm invention performance? *Journal of Product Innovation Management*, *39*(2), 222-264. https://doi.org/10.1111/jpim.12607
Coriat, B., Orsi, F., & Weinstein, O. (2003). Does biotech reflect a new science-based innovation regime? *Industry and Innovation*, *10*(3), 231-253.
D'Este, P., Llopis, O., Rentocchini, F., & Yegros, A. (2019). The relationship between interdisciplinarity and distinct modes of university-industry interaction. *Research Policy*, *48*(9), 103799. https://doi.org/10.1016/j.respol.2019.05.008
D'Este, P., & Patel, P. (2007). University–industry linkages in the UK : What are the factors underlying the variety of interactions with industry? *Research Policy*, *36*(9), 1295-1313. https://doi.org/10.1016/j.respol.2007.05.002
Fabrizio, K. R., & Di Minin, A. (2008). Commercializing the laboratory : Faculty patenting and the open science environment. *Research Policy*, *37*(5), 914-931. https://doi.org/10.1016/j.respol.2008.01.010
Fan, X., Yang, X., & Yu, Z. (2021). Effect of basic research and applied research on the universities' innovation capabilities : The moderating role of private research funding. *Scientometrics*, *126*(7), 5387-5411. https://doi.org/10.1007/s11192-021-03998-9
Foray, D., & Steinmueller, W. (2003). On the economics of R&D and technological collaborations : Insights and results from the project colline. *Economics of Innovation and New Technology*, *12*(1), 77-91.
Franzoni, C. (2009). Do scientists get fundamental research ideas by solving practical problems? *Industrial and Corporate Change*, *18*(4), 671-699. https://doi.org/10.1093/icc/dtp021

George, G., Zahra, S. A., & Wood Jr, D. R. (2002). The effects of business–university alliances on innovative output and financial performance : A study of publicly traded biotechnology companies. *Journal of business Venturing*, *17*(6), 577-609.
Georghiou, L. (1998). Global cooperation in research. *Research Policy, 27*(6), 611-626.
Gittelman, M., & Kogut, B. (2003). Does Good Science Lead to Valuable Knowledge? Biotechnology Firms and the Evolutionary Logic of Citation Patterns. *Management Science, 49*(4), 366-382.
Gonzalez-Brambila, C. N., Veloso, F. M., & Krackhardt, D. (2013). The impact of network embeddedness on research output. *Research Policy, 42*(9), 1555-1567.
Haeussler, C. (2011). Information-sharing in academia and the industry : A comparative study. *Research Policy*, *40*(1), 105-122. https://doi.org/10.1016/j.respol.2010.08.007
Haeussler, C., & Sauermann, H. (2013). Credit where credit is due? The impact of project contributions and social factors on authorship and inventorship. *Research Policy, 42*(3), 688-703. https://doi.org/10.1016/j.respol.2012.09.009
Haeussler, C., & Sauermann, H. (2020). Division of labor in collaborative knowledge production : The role of team size and interdisciplinarity. *Research Policy*, *49*(6), 103987. https://doi.org/10.1016/j.respol.2020.103987
Hameri, A.-P. (1996). Technology transfer between basic research and industry. *Technovation, 16*(2), 51-92. https://doi.org/10.1016/0166-4972(95)00030-5
Knoke, D., & Yang, S. (2008). *Social network analysis* (2nd éd.). Sage Publications.
Kolympiris, C., Kalaitzandonakes, N., & Miller, D. (2015). Location choice of academic entrepreneurs : Evidence from the US biotechnology industry. *Journal of Business Venturing, 30*(2), 227-254.
Laudel, G. (2002). What do we measure by co-authorships? *Research Evaluation*, *11*(1), 3-15. https://doi.org/10.3152/147154402781776961
Li, E. Y., Liao, C. H., & Yen, H. R. (2013). Co-authorship networks and research impact : A social capital perspective. *Research Policy*, *42*(9), 1515-1530.
Lim, K. (2004). The relationship between research and innovation in the semiconductor and pharmaceutical industries (1981–1997). *Research Policy, 33*(2), 287-321. https://doi.org/10.1016/j.respol.2003.08.001
Liu, H., Mihm, J., & Sosa, M. E. (2018). Where Do Stars Come From? The Role of Star vs. Nonstar Collaborators in Creative Settings. *Organization Science, 29*(6), 1149-1169. https://doi.org/10.1287/orsc.2018.1223
Martínez, C., Azagra-Caro, J. M., & Maraut, S. (2013). Academic Inventors, Scientific Impact and the Institutionalisation of Pasteur's Quadrant in Spain. *Industry & Innovation, 20*(5), 438-455. https://doi.org/10.1080/13662716.2013.824194
McFadyen, M. A., Semadeni, M., & Cannella, J. A. A. (2009). Value of Strong Ties to Disconnected Others : Examining Knowledge Creation in Biomedicine. *Organization Science*, *20*(3), 552-564.
Meyer, M. (2006). Are patenting scientists the better scholars? : An exploratory comparison of inventor-authors with their non-inventing peers in nano-science and technology. *Research Policy, 35*(10), 1646-1662. https://doi.org/10.1016/j.respol.2006.09.013
Mohnen, M. (2021). Stars and Brokers : Knowledge Spillovers Among Medical Scientists. *Management Science*. https://doi.org/10.1287/mnsc.2021.4032
Muriithi, P., Horner, D., Pemberton, L., & Wao, H. (2018). Factors influencing research collaborations in Kenyan universities. *Research Policy*, *47*(1), 88-97.
Oettl, A. (2012). Reconceptualizing Stars : Scientist Helpfulness and Peer Performance. *Management Science*, *58*(6), 1122-1140. https://doi.org/10.1287/mnsc.1110.1470

Paul-Hus, A., Mongeon, P., Sainte-Marie, M., & Larivière, V. (2017). The sum of it all : Revealing collaboration patterns by combining authorship and acknowledgements. *Journal of Informetrics, 11*(1), 80-87. https://doi.org/10.1016/j.joi.2016.11.005

Pavitt, K. (1991). What makes basic research economically useful? *Research Policy, 20*(2), 109-119. https://doi.org/10.1016/0048-7333(91)90074-Z

Perkmann, M., King, Z., & Pavelin, S. (2011). Engaging excellence? Effects of faculty quality on university engagement with industry. *Research Policy, 40*(4), 539-552. https://doi.org/10.1016/j.respol.2011.01.007

Perkmann, M., Salandra, R., Tartari, V., McKelvey, M., & Hughes, A. (2021). Academic engagement : A review of the literature 2011-2019. *Research Policy, 50*(1), 104114. https://doi.org/10.1016/j.respol.2020.104114

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A., Krabel, S., Kitson, M., Llerena, P., Lissoni, F., Salter, A., & Sobrero, M. (2013). Academic engagement and commercialisation : A review of the literature on university–industry relations. *Research Policy, 42*(2), 423-442. https://doi.org/10.1016/j.respol.2012.09.007

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational Collaboration and the Locus of Innovation : Networks of Learning in Biotechnology. *Administrative Science Quarterly, 41*(1), 116-145. https://doi.org/10.2307/2393988

Rotolo, D., Camerani, R., Grassano, N., & Martin, B. R. (2022). Why do firms publish? A systematic literature review and a conceptual framework. *Research Policy, 51*(10), 104606. https://doi.org/10.1016/j.respol.2022.104606

Rotolo, D., & Messeni Petruzzelli, A. (2013). When does centrality matter? Scientific productivity and the moderating role of research specialization and cross-community ties. *Journal of Organizational Behavior, 34*(5), 648-670.

Rybnicek, R., & Königsgruber, R. (2019). What makes industry–university collaboration succeed? A systematic review of the literature. *Journal of Business Economics, 89*(2), 221-250. https://doi.org/10.1007/s11573-018-0916-6

Salter, A. J., & Martin, B. R. (2001). The economic benefits of publicly funded basic research : A critical review. *Research Policy, 30*(3), 509-532. https://doi.org/10.1016/S0048-7333(00)00091-3

Sauermann, H., & Haeussler, C. (2017). Authorship and contribution disclosures. *Science Advances, 3*(11), e1700404. https://doi.org/10.1126/sciadv.1700404

Sauermann, H., & Stephan, P. (2013). Conflicting Logics? A Multidimensional View of Industrial and Academic Science. *Organization Science, 24*(3), 889-909. https://doi.org/10.1287/orsc.1120.0769

Shea, C. T., Menon, T., Smith, E. B., & Emich, K. (2015). The affective antecedents of cognitive social network activation. *Social Networks, 43*, 91-99.

Shichijo, N., Sedita, S. R., & Baba, Y. (2015). How does the entrepreneurial orientation of scientists affect their scientific performance? Evidence from the quadrant model. *Technology Analysis & Strategic Management, 27*(9), 999-1013. https://doi.org/10.1080/09537325.2015.1044959

Siegel, D. S. (2022). Two Cheers for RRBM, Pasteur's Quadrant, and an Application of RRBM to the Commercialization of Science and Technology Transfer. *Journal of Management Studies, 59*(6), 1643-1650. https://doi.org/10.1111/joms.12815

Soh, P.-H., & Subramanian, A. M. (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), 807-821. https://doi.org/10.1016/j.jbusvent.2013.11.001

Stokes, D. E. (2011). *Pasteur's Quadrant : Basic Science and Technological Innovation*. Brookings Institution Press.

Stuart, T. E., Ozdemir, S. Z., & Ding, W. W. (2007). Vertical alliance networks : The case of university–biotechnology–pharmaceutical alliance chains. *Research Policy*, *36*(4), 477-498.

Subramanian, A. M., Lim, K., & Soh, P.-H. (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), 595-612. https://doi.org/10.1016/j.respol.2012.12.002

Tartari, V., Perkmann, M., & Salter, A. (2014). In good company : The influence of peers on industry engagement by academic scientists. *Research Policy*, *43*(7), 1189-1203. https://doi.org/10.1016/j.respol.2014.02.003

Teodoridis, F., Bikard, M., & Vakili, K. (2019). Creativity at the Knowledge Frontier : The Impact of Specialization in Fast- and Slow-paced Domains. *Administrative Science Quarterly*, *64*(4), 894-927. https://doi.org/10.1177/0001839218793384

Tian, S., Xu, X., & Li, P. (2021). Acknowledgement network and citation count : The moderating role of collaboration network. *Scientometrics*, *126*(9), 7837-7857. https://doi.org/10.1007/s11192-021-04090-y

Tijssen, R. J. (2018). Anatomy of use-inspired researchers : From Pasteur's Quadrant to Pasteur's Cube model. *Research Policy*, *47*(9), 1626-1638.

Tushman, M., & O'Reilly, C. (2007). Research and Relevance : Implications of Pasteur's Quadrant for Doctoral Programs and Faculty Development. *The Academy of Management Journal*, *50*(4), 769-774.

Van Looy, B., Callaert, J., & Debackere, K. (2006). Publication and patent behavior of academic researchers : Conflicting, reinforcing or merely co-existing? *Research Policy*, *35*(4), 596-608. https://doi.org/10.1016/j.respol.2006.02.003

van Raan, A. F. J., & van Leeuwen, Th. N. (2002). Assessment of the scientific basis of interdisciplinary, applied research : Application of bibliometric methods in Nutrition and Food Research. *Research Policy*, *31*(4), 611-632. https://doi.org/10.1016/S0048-7333(01)00129-9

Walsh, J. P., Lee, Y.-N., & Tang, L. (2019). Pathogenic organization in science : Division of labor and retractions. *Research Policy*, *48*(2), 444-461. https://doi.org/10.1016/j.respol.2018.09.004

Yadav, A., McHale, J., & O'Neill, S. (2023). How does co-authoring with a star affect scientists' productivity? Evidence from small open economies. *Research Policy*, *52*(1), 104660. https://doi.org/10.1016/j.respol.2022.104660

Zucker, L. G., Darby, M. R., & Armstrong, J. (1998). Geographically Localized Knowledge : Spillovers or Markets? *Economic Inquiry*, *36*(1), 65-86. https://doi.org/10.1111/j.1465-7295.1998.tb01696.x

Figure 1. Stokes' quadrant model of scientific research (based on Stokes (2011, p. 73))

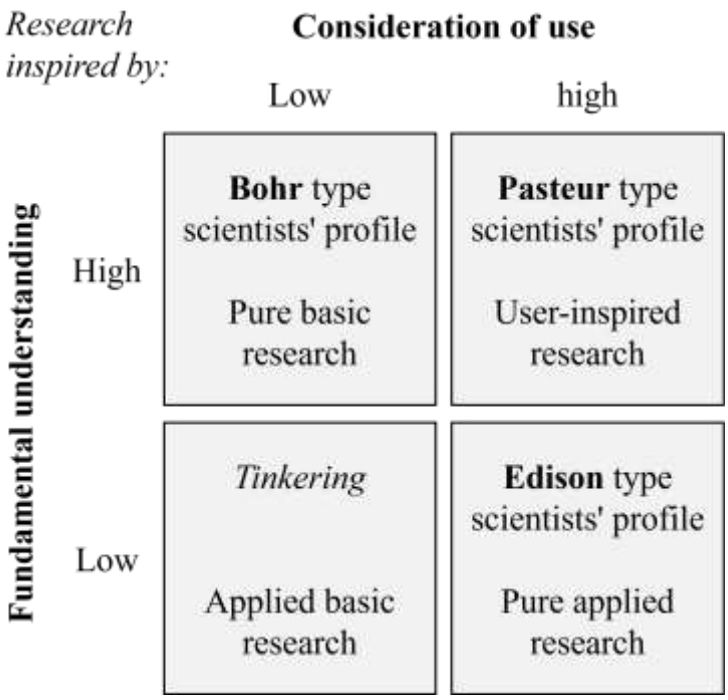

Figure 2. Distribution of scientists across profiles (based on Stokes' quadrant model of scientific research)

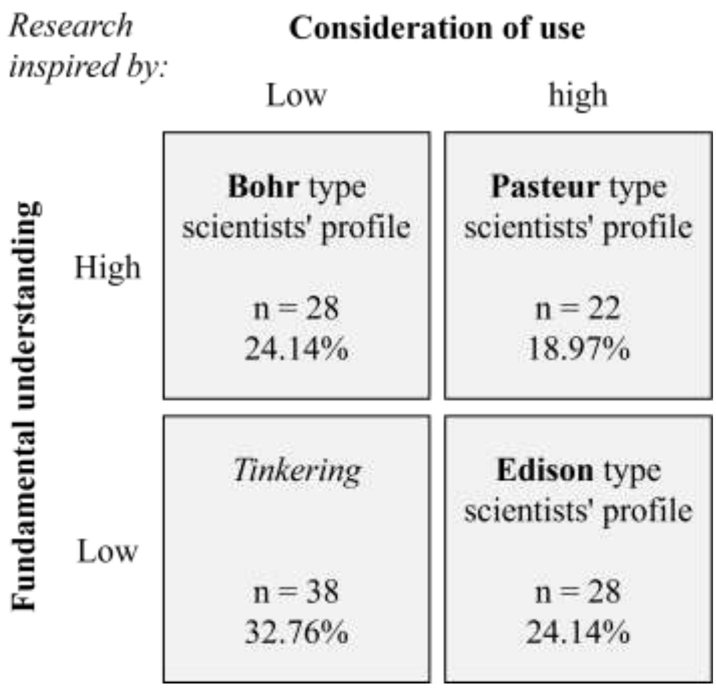

Table I. Correlations and descriptive statistics

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	**Male**	1.00																
2	**Professor**	0.06	1.00															
		0.56																
3	**Technical university**	0.07	-0.08	1.00														
		0.45	0.40															
4	**PhD abroad**	-0.11	-0.03	0.13	1.00													
		0.24	0.78	0.17														
5	**Post-doc abroad**	0.03	0.15	-0.18	0.19*	1.00												
		0.78	0.11	0.06	0.04													
6	**Large network**	-0.03	0.04	0.23*	0.16	-0.14	1.00											
		0.73	0.65	0.01	0.08	0.12												
7	**Informality (academia)**	-0.01	-0.19*	0.18	0.12	-0.03	0.3228*	1.00										
		0.90	0.05	0.05	0.19	0.78	0.00											
8	**Industrial**	0.14	0.15	0.20*	-0.01	-0.24*	0.44*	-0.12	1.00									
		0.12	0.11	0.03	0.95	0.01	0.00	0.18										
9	**Multiplexity**	0.00	0.03	-0.18*	-0.10	0.07	-0.09	0.01	-0.10	1.00								
		0.99	0.72	0.05	0.28	0.44	0.32	0.89	0.31									
10	**Scarcity**	-0.01	-0.16	-0.08	0.07	0.03	-0.20*	0.03	-0.22*	-0.26*	1.00							
		0.94	0.08	0.39	0.43	0.77	0.03	0.03	0.02	0.00								
11	**Knowledge**	0.06	0.07	-0.21*	-0.25*	0.07	-0.14	-0.10	-0.15	0.68*	-0.17	1.00						
		0.55	0.47	0.03	0.01	0.46	0.13	0.27	0.10	0.00	0.08							
12	**Idea**	0.02	-0.03	-0.15	-0.15	0.02	-0.12	0.03	-0.15	0.76*	-0.15	0.65*	1.00					
		0.86	0.72	0.11	0.12	0.80	0.21	0.77	0.10	0.00	0.11	0.00						
13	**Skill**	-0.06	0.06	-0.07	0.06	0.03	-0.04	0.15	-0.14	0.63*	-0.06	0.32*	0.45*	1.00				
		0.51	0.52	0.43	0.51	0.74	0.71	0.10	0.13	0.00	0.50	0.00	0.00					
14	**Equipment**	-0.01	-0.03	-0.05	0.03	0.03	0.09	0.07	0.07	0.54*	-0.14	0.13	0.19*	0.32*	1.00			
		0.93	0.78	0.60	0.72	0.77	0.31	0.49	0.48	0.00	0.13	0.18	0.04	0.00				
15	**Data**	-0.18	0.07	-0.12	0.08	0.10	0.03	-0.01	0.03	0.57*	-0.15	0.23*	0.23*	0.26*	0.40*	1.00		
		0.05	0.48	0.21	0.41	0.27	0.73	0.94	0.74	0.00	0.11	0.01	0.01	0.01	0.00			
16	**Funding**	0.10	-0.13	0.08	-0.02	-0.09	0.11	0.02	0.14	0.42*	-0.21*	0.12	0.19*	0.02	0.20*	0.26*	1.00	
		0.28	0.17	0.38	0.80	0.33	0.26	0.84	0.13	0.00	0.02	0.21	0.04	0.82	0.03	0.01		
17	**Fun**	0.07	0.09	-0.21*	-0.14	0.11	-0.23*	-0.08	-0.11	0.70*	-0.27*	0.43*	0.44*	0.27*	0.22*	0.22*	0.26*	1.00
		0.46	0.34	0.03	0.15	0.25	0.01	0.40	0.26	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.01	
	Obs	116	116	116	116	116	116	116	116	116	116	116	116	116	116	116	116	116
	Mean	0.88	0.43	0.30	0.23	0.53	0.18	0.22	0.19	3.14	0.77	0.78	0.66	0.51	0.29	0.19	0.22	0.50
	Std. Dev.	0.33	0.50	0.46	0.42	0.50	0.39	0.20	0.20	1.21	0.91	0.26	0.32	0.28	0.25	0.24	0.20	0.36
	Min	0	0	0	0	0	0	0	0	0.80	0.00	0.09	0	0	0	0	0	0
	Max	1	1	1	1	1	1	1	1	6.20	3	1	1	1	1	1	1	1

Table II. Description of the differences across the four Stokes quadrants

	Variable (average)	Category				Analysis of variance		
		Bohr	Edison	Pasteur	rest			
	n	28	28	22	38	F-statistic	p-value	Sig.
Descriptive	Career duration	22.82	19.89	25.55	23.63	0.86	0.46	
	Female	17.86%	10.71%	9.09%	10.53%	0.39	0.76	
	Technical university affiliation	17.86%	39.29%	40.91%	26.32%	0.02	0.21	
	Professor status	50.00%	25.00%	59.09%	42.11%	2.25	0.09	*
	PhD abroad	25.00%	17.86%	27.27%	23.68%	0.23	0.88	
	Post-doc abroad	78.57%	32.14%	63.64%	44.74%	5.24	0.00	***
Industry relation	Patent(s)	25.00%	57.14%	77.27%	47.37%	5.22	0.00	***
	Part time in industry	3.57%	14.29%	9.09%	7.89%	0.68	0.57	
	Spin-off creation	3.57%	14.29%	36.36%	13.16%	3.73	0.01	**
	Industrial funding	3.57%	25.00%	27.27%	15.79%	2.20	0.09	*
	Use industrial knowledge	7.14%	17.86%	18.18%	18.42%	0.65	0.59	
Network	Network size	7.79	9.46	10.73	8.42	2.72	0.05	*
	Network size (academic)	7.11	6.71	7.41	6.39	0.96	0.42	
	Network size (industrial)	0.68	2.75	3.32	2.03	5.61	0.00	***
	Network size (formal)	4.86	5.61	6.36	5.16	3.08	0.03	**
	Network size (informal)	2.93	3.86	4.36	3.26	1.08	0.36	
Network characteristics	Same affiliation	46.48%	41.90%	33.29%	33.26%	1.74	0.16	
	Affiliation abroad	38.67%	21.32%	39.40%	30.19%	2.85	0.04	**
	Male	72.98%	72.33%	76.41%	69.43%	0.59	0.62	
	PhD students	20.51%	9.41%	20.72%	18.78%	2.09	0.11	
	PhD supervisor	2.78%	10.38%	2.52%	3.95%	3.22	0.03	**
	Short-term relationships	9.03%	7.14%	8.33%	13.18%	0.89	0.45	
	Long-lasting relationships	65.54%	64.59%	69.95%	59.70%	0.74	0.53	
Resources	Multiplexity	3.36	3.01	3.26	3.01	0.62	0.60	
	Scarcity	0.79	0.86	0.59	0.79	0.37	0.77	
	Knowledge	76.99%	80.90%	75.83%	77.94%	0.18	0.91	
	Idea	71.11%	66.68%	62.55%	62.24%	0.50	0.68	
	Skill	62.00%	39.05%	51.81%	50.53%	3.23	0.03	**
	Equipment	28.71%	23.95%	38.32%	28.52%	1.43	0.24	
	Data	19.34%	12.80%	19.79%	21.85%	0.77	0.51	
	Funding	14.53%	27.97%	25.61%	21.19%	2.48	0.07	*
	Fun	63.12%	49.64%	52.03%	39.10%	2.51	0.06	*

Table III. Results of the multinomial logit regression analyses on resources multiplexity and scarcity

	Bohr vs. Tinkering		Edison vs. Tinkering		Pasteur vs. Tinkering		Edison vs. Bohr		Pasteur vs. Bohr		Pasteur vs. Edison	
Controls												
Male	-0.61	(0.85)	0.10	(0.86)	0.01	(1.00)	0.71	(0.97)	0.62	(1.05)	-0.09	(1.07)
Professor	0.81	(0.61)	-0.84	(0.59)	0.49	(0.60)	-1.65**	(0.71)	-0.32	(0.69)	1.33**	(0.67)
Technical university	-0.06	(0.75)	0.62	(0.60)	0.82	(0.64)	0.68	(0.79)	0.88	(0.80)	0.20	(0.67)
PhD abroad	-0.37	(0.68)	-0.65	(0.72)	-0.20	(0.71)	-0.28	(0.82)	0.17	(0.78)	0.45	(0.80)
Post-Doc abroad	1.62**	(0.67)	-0.27	(0.57)	0.95	(0.62)	-1.89**	(0.73)	-0.67	(0.77)	1.22*	(0.66)
Network												
Large network	0.13	(1.42)	1.24*	(0.75)	1.13	(0.81)	1.11	(1.43)	1.00	(1.43)	-0.11	(0.81)
Informality (academia)	2.78**	(1.32)	-0.81	(1.27)	-0.52	(1.45)	-3.59**	(1.49)	-3.30**	(1.58)	0.29	(1.56)
Industrial	-7.23***	(2.74)	0.50	(1.52)	0.60	(1.81)	7.74***	(2.87)	7.83***	(2.95)	0.10	(1.96)
Resources												
Multiplexity	0.13	(0.25)	0.13	(0.25)	0.25	(0.25)	-0.01	(0.29)	0.11	(0.27)	0.12	(0.28)
Scarcity	-0.07	(0.32)	0.25	(0.31)	0.00	(0.37)	0.32	(0.36)	0.07	(0.40)	-0.25	(0.40)
Constant	-1.50	(1.37)	-0.77	(1.34)	-2.54*	(1.53)	0.73	(1.56)	-1.04	(1.66)	-1.76	(1.65)
Nb. of observations	116											
Log likelihood	-132.46***											
LR chi 2 (30)	52.25											
Pseudo R^2	0.16											

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table IV. Results of the multinomial logit regression analyses on resources types

	Bohr vs. Tinkering		Edison vs. Tinkering		Pasteur vs. Tinkering		Edison vs. Bohr		Pasteur vs. Bohr		Pasteur vs. Edison	
Controls												
Male	-0.88	(1.02)	-0.50	(0.94)	-0.52	(1.05)	0.37	(1.18)	0.35	(1.17)	-0.02	(1.15)
Professor	1.04	(0.77)	-0.92	(0.67)	0.68	(0.65)	-1.97**	(0.88)	-0.37	(0.83)	1.60**	(0.76)
Technical university	-0.33	(0.94)	0.41	(0.64)	0.86	(0.66)	0.74	(1.02)	1.19	(0.99)	0.45	(0.72)
PhD abroad	-1.05	(0.88)	0.25	(0.80)	-0.28	(0.75)	1.29	(1.06)	0.77	(0.95)	-0.53	(0.90)
Post-Doc abroad	2.18**	(0.85)	-0.58	(0.66)	1.03	(0.66)	-2.76***	(0.95)	-1.15	(0.92)	1.61**	(0.74)
Network												
Large network	1.44	(1.74)	1.53*	(0.81)	1.43	(0.88)	0.09	(1.74)	-0.01	(1.71)	-0.10	(0.87)
Informality (academia)	2.96*	(1.55)	-0.98	(1.37)	-0.78	(1.50)	-3.94**	(1.81)	-3.74**	(1.81)	0.20	(1.68)
Industrial	-9.41***	(3.45)	0.69	(1.70)	0.05	(2.01)	10.10***	(3.62)	9.46***	(3.62)	-0.64	(2.21)
Resources												
Knowledge	-5.28**	(2.34)	1.61	(1.57)	-0.96	(1.70)	6.89***	(2.54)	4.32*	(2.51)	-2.57	(1.92)
Idea	2.10	(1.62)	0.17	(1.18)	0.14	(1.40)	-1.92	(1.70)	-1.95	(1.80)	-0.03	(1.48)
Skill	1.15	(1.34)	-2.65**	(1.34)	-0.48	(1.42)	-3.80**	(1.55)	-1.64	(1.54)	2.16	(1.58)
Equipment	-1.49	(1.68)	-0.61	(1.37)	1.55	(1.34)	0.89	(1.87)	3.05*	(1.80)	2.16	(1.51)
Data	-0.67	(1.64)	-2.83*	(1.59)	-1.95	(1.58)	-2.16	(2.07)	-1.29	(1.90)	0.88	(1.92)
Funding	-3.76	(2.33)	1.28	(1.71)	1.06	(1.80)	5.04**	(2.55)	4.82**	(2.47)	-0.22	(1.90)
Fun	4.24***	(1.32)	2.00*	(1.03)	1.75	(1.13)	-2.25*	(1.35)	-2.49*	(1.47)	-0.25	(1.15)
Constant	-0.11	(1.69)	-0.40	(1.50)	-1.53	(1.62)	-0.30	(1.92)	-1.42	(1.93)	-1.12	(1.80)
Nb. of observations	116											
Log likelihood	-114.10***											
LR chi 2 (45)	88.96											
Pseudo R^2	0.28											

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Appendix A. Definitions of variables

Name	Description
Scientist quadrant	Categorical variable coded '1' if the respondent display a Bohr research profile, '2' for an Edison research profile, '3' for a Pasteur research profile, and '4' for the tinkering category.
Male	Dichotomous variable coded '1' if the respondent is a man, and '0' if the respondent is a woman
Career duration	Count variable of the number of years since the respondent obtained their Ph.D.
Professor	Dichotomous variable coded '1' if the respondent has a professor status (professor, full professor, emeritus professor), and '0' if the respondent has another status (assistant professor, associate professor, researcher, or another status)
Technical university	Dichotomous variable coded '1' if the respondent's main affiliation in a technical university, '0' if the respondent's main affiliation in a research university or an affiliation outside university
PhD abroad	Dichotomous variable coded '1' if the respondent obtained a Ph.D. outside The Netherlands, and '0' if the Ph.D. was obtained in The Netherlands
Post-doc abroad	Dichotomous variable coded '1' if the respondent had a post-doc experience outside The Netherlands, and '0' otherwise
Network size	Count variable of the number of contacts listed in the research network
Informality (academia)	Measured as the percentage of informal contacts listed in the academic research network
Industrial	Measured as the percentage of industrial contacts listed in the research network
Multiplexity	Measured as the average number of resources contributed per contact in the research network
Scarcity	Count variable of the number of resources provided by only one contact in the research network
Knowledge **Idea** **Skill** **Equipment** **Data** **Funding** **Fun**	A series of seven measures of the percentage of contacts providing the resource in the research network

Appendix B. Resource items

Resource item	Description
Knowledge	This colleague had knowledge and experience on the research topic.
Idea	This colleague brought creative ideas on research directions to pursue.
Skill	This colleague brought skills in specific experimental or analytical techniques.
Equipment	This colleague enabled access to equipments and instruments.
Data	This colleague facilitated access to data.
Funding	This colleague provided access to funding.
Fun	This colleague brought fun, energy and motivation to get started and conduct the research.