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Knowledge production and the structure of collaboration networks in two scientific fields

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Abstract In this paper the relationship between knowledge production and the structure of research networks in two scientific fields is assessed. We investigate whether knowledge production corresponds positively or negatively with different types of social network structure. We show that academic fields generate knowledge in different ways and that within the fields, different types of networks act as a stimulant for knowledge generation.

Keywords Knowledge production · Research collaboration · Social network analysis · New sciences · Nanoscience · Astrophysics

Introduction

The production of new knowledge is one of the central functions of research and science.[1] The conditions under which scientists develop and produce such new knowledge have long been the topic of debate. Recent studies have shown that there is no universal model of scientific production that holds true across all scientific fields but that different scientific fields generate knowledge in different ways and are subject to different knowledge dynamics. Bonaccorsi (2007, 2008) suggested that different knowledge fields evolve under

[1] We are aware and indeed have highlighted the fact in previous publications, that knowledge generation is not the only task of researchers. Rather, research output is multidimensional and research groups do specialize in different outputs dimensions such as education of new scientists or the maintaining of research infrastructure (Jansen et al. 2007, Schmoch et al. 2009). However, in this paper we concentrate only on the production of new knowledge as one of the core tasks of science because the relationship between knowledge production and network structure has in the past been made repeatedly.

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different dynamics in terms of their growth, their convergence and their complementarities. He highlights the role of distinct cognitive characteristics of fields in the way that knowledge is produced in these fields. In doing so he differentiates between two broadly different types of science: the old, established and the new sciences. New sciences are sciences that developed after the Second World War such as computer or information science whilst old, established sciences are those that originated after the seventeenth century scientific revolution such as chemistry, mathematics or physics. The emergence of new scientific fields is thought to have been accompanied by the displacement of the traditional "mode 1" of knowledge production by a "mode 2" of knowledge production (Gibbons et al. 1994). In the new sciences, "mode 2" knowledge production is thought to take place in a transdisciplinary manner, spanning boundaries between academic fields and between basic and applied science. In contrast, "mode 1" knowledge production is typically thought to be disciplinary, to be concerned with basic science and to occur predominantly in the old established big sciences. However, exactly which scientific fields actually follow a "mode 2"-logic is so far empirically unresolved (Jacob 2001); (Jansen et al. 2009); (Hessels and van Lente 2008).

Combining the concepts of "new science" versus "old science" and "mode 1" versus "mode 2 knowledge production", it seems likely that different kinds of knowledge dynamics correspond with different types of underlying research networks. That research networks play a crucial role in the production of knowledge has long been understood. However, there is controversy over exactly which type of network structure generates positive outcomes for social actors. This controversy becomes especially manifest in two conflicting theories concerning the optimal social structure facilitating innovation and the production of knowledge (Jansen 2002, 2004). Following Coleman (1988), densely embedded closed networks are advantageous because they foster the development of mutual trust and forestall opportunism. Burt (1992, 2004) in contrast, argues that brokerage opportunities arise in open social structures which contain multiple disconnected clusters allowing for what he termed "structural holes". The open structures benefit innovative output because they link otherwise unconnected actors and provide advantage in the form of rapid access to novel information resulting in an information and control advantage compared to others. A more recent discussion focuses on the question of whether there is a trade-off between redundant and non-redundant contacts in social networks, that depends on exchange mechanisms and the kind of resources that are exchanged (Reagans and Zuckerman 2008). In our paper we try to determine whether scientific productivity in new and/or established scientific fields is dependent on different types of underlying research collaboration networks.

In a previous study, Heinze and Bauer (2007) have shown that in nanoscience the existence of structural holes in a network has a positive effect on researchers' citation scores, and indirectly also a positive effect on their individual research creativity. Our study tests the influence of network structure not on research creativity but on scientific performance. It does so with respect to research groups as opposed to the individual scientist. Furthermore, we compare the effect of structural holes in two different research fields; the aim being to clarify whether the relationship of research productivity and network structure is field specific. To do this, we chose two natural science fields that differ in their cognitive structures and therefore in the way in which knowledge is produced. One of these, astrophysics, is considered an established big science field, whilst the other one, nanoscience, is considered a dynamic new science field (Bonaccorsi 2007, 2008).

In "Network structure and good ideas: structural holes versus network closure" section of this paper, we give a short overview of the conflicting theoretical positions concerning social networks and innovation. In "The dynamics of science " section, we briefly describe the way in which the dynamics of science differ between scientific fields. In "Objectives" section, our hypotheses and our objectives are more precisely defined, and in "Research design" section, the research design is explained. We then, in "Description of the scientific fields" section, describe the way knowledge is produced in the two fields, astrophysics and nanoscience, and the role that collaboration networks play. In "Effect of network structure on knowledge production" section, our statistical model is presented and interpreted. In conclusion, we discuss the results.

Network structure and good ideas: structural holes versus network closure

The production of new knowledge is one of the core tasks of research and science. It has long been known that personal and organisational networks play a crucial role in the production of such new knowledge, the fostering of innovations and the development of new creative ideas (Jansen 2004). Networks bring heterogeneous knowledge together (Weyer 2000), facilitate the flow of information and exchange of ideas (Burt 1992) and provide a basis for cooperation between otherwise unconnected partners (Coleman 1988). In general, networks facilitate a balance between cooperation (which requires trust) and competition; they combine attributes of the market (autonomous actors) with attributes of hierarchical structures (the ability to pursue collective/shared goals) (Mayntz 1992; Powell 1990). In addition, tacit knowledge (Polanyi 1985) which is inherent in people and can only be accessed through personal contact is especially dependent on, and can only be acquired through, social networks. Thus networks provide an important arena for the novel combination of diverse knowledge (Heidenreich 2000). They bring together heterogeneous actors and can facilitate relationships that are mutually enriching and complement one another. The "coupling of complementary resources" (Weyer 2000, p. 6) allows actors in a network to concentrate on their area of expertise and to enhance their performance in this area. No resources have to be wasted in bringing in skills of other complementary fields. Thus ones own strengths can be accentuated while weaknesses can be minimised. If complementary competencies and resources can be used in an efficient manner, then redundancies can be avoided. Also, networks lower the risk of an investment significantly since the risk is shared between the partners, which allows for highly specialised investments.

The exact type of network structure that will be beneficial for the process of knowledge production is, however, still a matter of controversy. Granovetter (1973) promoted the idea of "the strength of weak ties", meaning that network relations that are rather loose and not very intense allow for the most diverse knowledge and information to be accessed and thus foster innovation processes. In fact, innovation is often thought to occur in networks with weak ties; for example, Burt (2004) conducted a study of innovation output of managers in a large electronics company. He found that people positioned near the holes in a social structure have an increased likelihood of having good ideas (Burt 2004, p. 349). In his opinion the brokerage advantages that arise from structural holes affect performance mainly through "vision advantage" (Burt 2004, p. 351). He states that "[…] people whose networks bridge the structural holes between groups have earlier access to a broader diversity of information and have experience in translating information across groups […]. [They] have an advantage in detecting and developing rewarding opportunities. Information arbitrage is their advantage. They are able to see early, see more broadly, and translate information across groups. […] brokerage across structural holes between groups provides a vision of options otherwise unseen" (Burt 2004, p. 354). He stresses the value of information as a network resource. Novel ideas often involve the combination of bits of knowledge across groups (Burt 2004, p. 356). Burt also points out that the more people specialise, the higher the value of complementary ideas and information because “it is impossible to keep up with developments in other specialities […]. So there is a market for the information arbitrage of network entrepreneurs […]” (Burt 2004, p. 389). Jansen (1996) also points out that weak ties foster—next to one’s own research efforts—the build-up of “absorptive capacity”, i.e. the ability to appropriate research ideas and results from others (Cohen and Levinthal 1990).

Strong ties, as the opposite of weak or loose ties, are thought by some to lead to stagnation and to an ignorance and oversight of new ideas, thus inhibiting creativity and innovation. Grabher (1993) conducted a study of the decline of the industry in the German “Ruhrgebiet” and claimed that the complacency and self-satisfaction that accompany strong local ties were a major factor for the degeneration of the heavy industry in the area. Werle (1990) came to a similar conclusion concerning the innovative capacity of the German telecommunication systems in the 1980s, blaming the densely interlocking ties between telecommunication operators and component suppliers for stifling innovation.

However, some studies looking at the relationship between network structure and innovation output have come to exactly the opposite, contrary conclusions. Walker et al. (1997) conducted an analysis of the formation of an industry network in the field of biotechnology. They looked at the way start-up companies develop new relationships and how these relationships develop over time. They found that closed social networks with strong ties are a far greater driving force behind the formation of networks than the strategic network formation allowing for and bridging structural holes. Also for example, Ahuja (2000) conducted a study on innovation output of firms in the chemical industry and found there to be a negative effect of structural holes on innovation. According to Coleman (1988), social capital—i.e. capital that is embedded in relations among actors—arises not from open networks but from network closure. In closed social networks trust between partners can be built up and the partners bind themselves to each other through mutual obligations and expectations. Thus, according to Coleman it is the closed social networks that make possible and facilitate cooperation among actors. A recent simulation study by Reagans and Zuckerman (2008) shows that when demand for knowledge is homophilic and information from a small social distance is valued highly, positions in closed networks can excel broker positions. However, if there is a demand for diverse information, then the establishment of non-redundant network ties will be more successful.

It cannot therefore be claimed for certain whether strong or weak ties, closed networks or networks with structural holes are beneficial to the innovation process. Jansen (1996) concludes that in principle the more turbulent and unpredictable the environment and the stronger the interdependencies and synergies are between the partners, the more successful are innovation strategies and absorptive capacity relying on weak ties. Ahuja (2000, p. 451) thinks that if “developing a collaborative milieu and overcoming opportunism are essential to success, closed networks are likely to be more beneficial” but whenever “speedy access to diverse information is essential, structural holes are likely to be advantageous”. In a more recent paper Yayavaram and Ahuja (2008) come to the conclusion that in innovation processes a modularized structure of the knowledge base of firms combining dense knowledge clusters with a few linkages between them enhances innovation and creativity. Thus, it seems most likely that the optimal social network structure for the production of knowledge can only be determined and understood relative to a particular context.

The dynamics of science

Different science fields follow different dynamics, have different cognitive structures and thus generate knowledge in a different manner. Whitley (1984/2000) suggested that differences and changes in scientific knowledge can be understood in terms of differences and changes in the system of their production and evaluation. According to Whitley, fields differ in terms of "mutual dependence" (functional, strategic) and "task uncertainty" (technical, strategic). Bonaccorsi (2008) proposed an overlapping characterisation of science fields by rate of growth, degree of convergence or divergence and types of cognitive, technical and institutional complementarities that helps to explain the differences. Synthesizing both authors the dynamics of science fields can be differentiated in three dimensions:

1. the rate of growth; i.e. the capacity of scientific fields to survive and/or to prosper,
2. the relative degree of convergence or divergence; i.e. the way in which knowledge flows within fields. Convergent fields exhibit a strong mutual dependence of scientists and a low task uncertainty, while divergent fields show less mutual dependence with a high task uncertainty,
3. the types of cognitive, technical and institutional complementarities; i.e. the different needs for shared infrastructures, collaboration patterns, and institutional embedding of scientific fields.

Both, Whitley and Bonaccorsi, emphasize that the differences in knowledge dynamics can be explained through internal differences of scientific fields. Bonaccorsi distinguishes scientific fields along a time axis. Those scientific fields that developed after the seventeenth century scientific revolution (astronomy, chemistry, mathematics and physics) and those that evolved after the Second World War (computer or information science, life sciences based on molecular biology, materials science, etc.) (Bonaccorsi 2008, pp. 285–286). He terms them "old, established sciences" and "new sciences". Bonaccorsi (2008) posits that old and new sciences are distinctively different in terms of their rate of growth, their degree of internal diversity and the nature of complementarity. New sciences are thought to grow more than the average at aggregate level, and to follow divergent rather that convergent search regimes. They have a greater need for cognitive complementarity as their research topics cut across different layers of complex hierarchical systems and lie at the interface between the natural and the artificial. Also, they need different technical facilities: where old sciences require either large and dedicated facilities or small scale laboratories, new sciences need medium-sized, general purpose facilities. Last but not least, "new sciences are intrinsically based on institutional complementarities" (Bonaccorsi 2008, p. 307); i.e. they require the contributions of scientists working in different institutional environments, bringing in different types of data and experience.

While Bonaccorsi and Whitley highlight the importance of cognitive characteristics of scientific fields, the so called mode-2 approach of knowledge production (Gibbons et al. 1994) emphasizes the changes that are occurring outside science. According to Gibbons et al. (1994), knowledge produced in this "mode 2" forms in an application-context, is oriented towards problem solving, and is transdisciplinary in nature. The search for knowledge is application-driven, i.e. looking at the utilisation of knowledge with a view to solving specific practical problems. Traditional, truth-oriented scientific quality criteria are being replaced by pragmatic, demand-driven criteria of functionality as defined by the stakeholders. Accordingly, this way of producing knowledge involves a continuous exchange with stakeholders (e.g. the public). To what extent this new mode of knowledge production applies to different scientific disciplines is a question that has yet to be answered, and at the moment is lacking empirical grounding (Jacob 2001; Jansen et al. 2009; Hessels and van Lente 2008).

Objectives

We analyse the effect of network structure on performance by concentrating on the scientific output of researchers from two mutually exclusive natural scientific fields: those of astrophysics and nanoscience. Astrophysics was chosen as an "established big science" and a field primarily concerned with basic research; nanoscience was chosen as one of the so called "new sciences" and a field not purely concerned with basic research but also with an apparent application orientation. As context we regard the specific modes of knowledge production and cognitive structures in these scientific fields. We follow Bonaccorsi (2008) and Whitley (1984/2000) in formulating two hypotheses describing the knowledge production in the fields:

H1a Astrophysics is an established natural science field that is paradigmatic and follows long-term stable research programs. Thus technical and strategic task uncertainty is quite low whilst mutual dependence, e.g. concerning access to large facilities is very high.

H1b Nanoscience is a rapidly developing new field with new research questions and approaches emerging very fast. High divergence of research paths and high growth rates mean that technical and strategic task uncertainty is high whilst mutual dependence e.g. with respect to collaboration with highly specialized experts is lower.

Concerning the optimal social network structure that facilitates knowledge production in these two fields we draw the following concurring three hypotheses from the debate outlined in "Network structure and good ideas: structural holes versus network closure" section:

H2 The lower the network constraint, the higher the gains from the network and the higher the productivity of researchers.

Following Burt (1992), research networks should further the productivity of researchers in so far as the network is not concentrated directly or indirectly on a single contact. These network-configurations grant advantages in the form of information and control to certain actors in a network—i.e. the lower the network constraint, the higher the gains from the network and the higher the productivity of researchers.

H3 The higher the network constraint, the higher the gains from the network and the higher the productivity of researchers

According to Coleman (1988) it should be the dense interconnected networks that grant advantages for the innovation output because they foster the development of trust and thus help overcome opportunistic behaviour and thereby lower the risk of close collaboration. Thus, the higher the network constraint, the higher the gains from the network and the higher the productivity should be.

H4 The optimal structural design is context dependent and contingent on the actions that the structure seeks to facilitate.

The lower uncertainties and the stronger dependencies, the more closed networks facilitate knowledge production and foster performance. The higher uncertainties and the lower dependencies, the more open networks and structural holes enhance knowledge production and performance. With our paper we aim to test the explanatory power of the two conflicting structural theories on network effects (H2, H3). Following Ahuja (2000) and Reagans and Zuckerman (2008), we believe that the expediency of the two theories is context dependent and contingent on the type of information that needs to be exchanged (H4). We hope to resolve some controversies on their applicability in the area of science by introducing the type of knowledge production as an interacting factor.

Research design

Publication data was collected via the Science Citation Index. The fields were identified with the help of a keyword-based search strategy.[2] Such a keyword-based search strategy provides a more precise insight than an identification based on subject categories for journals, as for example in the "Web of Science", because articles are directly assigned to a specific discipline rather than being indirectly assigned with respect to the type of journal they are published in.

To establish the relationship between knowledge production and network structure, data for German research groups working in astrophysics and nanoscience was collected by our research team. The identification of the population of research groups for the two fields was completed in two steps (cf. (Wald et al. 2007). In a first step, a bibliometric analysis of the Science Citation Index (SCI) revealed all researchers that published at least one article in the field. Since the SCI-data are based on individuals, the actual affiliations of researchers to research groups had to be uncovered with the help of secondary information from directories and web pages. A research group was defined as the smallest stable unit within an organisation that conducts research. It often corresponds to a formal organizational unit, e.g. a chair or a subdivision, but this must not necessarily be the case. In a second step, the group-level list was validated by experts from the different fields. For the nanoscience and the astrophysics sample this was done by the funding agencies of the Federal Ministry of Education and Research which manage the funding programs relevant for nanoscience respectively astrophysics. This two-step procedure led to a total population of 223 research groups in nanoscience and 122 in astrophysics. From the total population thus determined a random sample of 25 research groups in astrophysics and 27 research groups in nanoscience was drawn.

A qualitative explorative study based on face-to-face-interviews with the leaders of these research groups was conducted in 2004 in which they were asked about their collaboration networks as well as their network and research strategies. Based on the qualitative analysis of these interviews (Franke et al. 2006) a standardized questionnaire was developed with which the research groups were polled again in 2006/2007. This was accompanied by a qualitative semi-structured phone-interview in which the composition of the collaboration-networks of the research groups was gathered. The network data were collected as ego-centred networks; that is, alter-ego and alter-alter data were collected.[3]

[2] The key-word based search strategy was developed by the Fraunhofer Institute for Systems and Innovation Research ISI. The authors would especially like to thank Ulrich Schmoch and Torben Schubert for collating and providing the relevant data.

[3] A more detailed description of this qualitative way of gathering ego-centred network data is given in Franke and Wald (2006).

Table 1 Population and sample

	Astrophysics		Nanoscience	
	Population	Sample	Population	Sample
University	67 (56.4%)	16 (50.0%)	143 (64.1%)	25 (69.4%)
Max-Planck-Society (MPG)	38 (31.1%)	7 (21.9%)	29 (13.0%)	4 (11.1%)
Leibniz-Association (WGL)	2 (1.6%)	2 (6.3%)	6 (2.7%)	1 (2.8%)
Helmholtz-Association (HGF)	5 (4.0%)	1 (3.1%)	16 (7.2%)	2 (5.6%)
Fraunhofer-Association (FhG)	0 (0.0%)	0 (0.0%)	7 (3.1%)	1 (2.8%)
Other	10 (8.3%)	6 (18.8%)	22 (9.8%)	3 (8.3%)
Total	122	32	223	36

Sixty-five percent of the original sample answered in 2006/2007 (18 research groups in astrophysics, 16 in nanoscience), the missing thirty-five percent were replaced by a new random sample from the original population.

The network data used for our analyses is made-up of research groups from the first and second wave of the panel study. Whenever available the newer network data from 2007 was used (50 cases), in addition 18 research groups from the 2004 panel wave who did not participate in the 2007 wave, were added to the data set. So in total we have data for 68 research groups (36 in nanoscience and 32 in astrophysics) who were polled either in 2004 or 2006/07. Table 1 shows the composition of our sample in comparison to the population.

Both, universities and extra-university institutions are part of the sample. A comparison of the institutional composition of the sample with the population shows that the make-up of the sample is similar to that of the population, and that the different kinds of institutions into which the German extra-university research system is differentiated are represented. There is a small bias in the under-representation of universities and research groups from Max-Planck-Societies and an over-representation of other extra-university research institutes in astrophysics; in nanoscience there is a small bias in the opposite direction regarding the number of research groups from universities.

Description of the scientific fields

In the description of the two scientific fields, we first present the collected bibliometric data to characterise the fields and to highlight their different dynamics. For both fields, this is then followed by a description of the type of network structure that we found in our sample of research groups in Germany.

Dynamics and subject matter

Astrophysics is concerned with the study of the physical, chemical or meteorological properties of celestial objects (stars, planets, comets, galaxies, interstellar matter, black holes etc.) and their movement. It determines and analyses the physical laws ruling the origin, evolution and development of the universe, or of large-scale structures like galaxies and galaxy groups. This is done by observation with earth-bound and sky telescopes using a large range of electromagnetic wavelength (radio-, infrared-, optical- and ultraviolet astronomy). Observations are predicted or interpreted with the help of theoretical models and/or numerical simulations with high-capacity computers. Astrophysics has a history

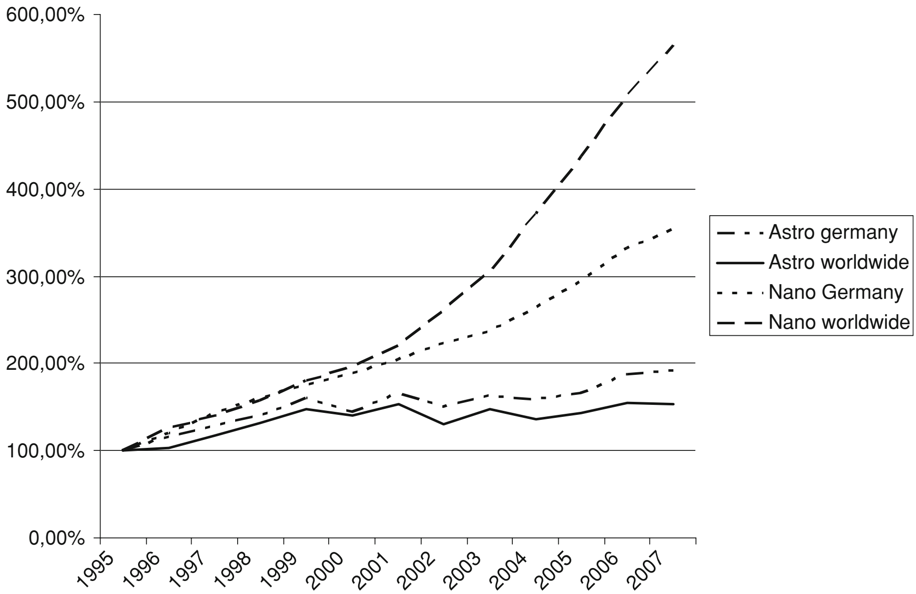

Fig. 1 Percentage of publications in astrophysics and nanoscience in Germany and worldwide (*Source*: SCISEARCH (STN), Calculations of the Fraunhofer ISI)

reaching long back into the development of mankind. Astrophysics was already a cooperative and professionalized science with research funding and research awards in the eighteenth century. A big part of the governmental support for astrophysics at this time was due to the application possibilities of astrophysics (especially navigation) (Beaver and Rosen 1978). Nowadays astrophysics is considered a basic science, although the development of scientific instrumentation can have an indirect positive effect on technological advances. Unlike most young sciences growing at exponential rates (de Solla Price 1963), a look at the growth of the number astrophysical publications in the last twelve years shows that the field has reached a saturation, although in the German case, the growth rate is higher (cf. Fig. 1).

Nanoscience deals with materials and systems at the nanoscale level. The term “nano” describes one part in a billion of a unit (10^{-9}); thus one billion nanometers add up to one meter. The core subject matter of nanoscience is the discovery of new behaviours and properties of systems/materials which depend on the nanoscale effects of their components (Bachmann 1998). Nanoscience includes the creation, analysis and application of structures and molecular materials with the aim of generating hitherto unknown materials and structures with specific, novel characteristics.

The definition of nanotechnology by the American National Nanotechnology Initiative (NNI) includes the following: [4]

- Research and technology development at the atomic, molecular or macromolecular levels, in the 1–100 nm range.
- Creating and using structures, devices and systems that have novel properties and functions because of their small and/or intermediate size.
- Ability to control or manipulate materials or systems at the atomic scale.

[4] Compare http://www.nano.gov/html/facts/whatIsNano.html (as at July 10, 2008).

Research at this scale became possible mainly through the invention of the Scanning Tunnelling Microscope (STM) in 1981 which allows for the positions of individual atoms to be identified and visualised (Mody 2004). For the first time it became possible "to manipulate *and* observe matter at lower levels of resolution *at the same time*" (Bonaccorsi 2008, p. 294). The birth of the field of nanoscience, however, is thought to have occurred more than 20 years before the relevant instruments and technology became available. In a speech at a meeting of the American Physical Society in December 1959, the physicist and Nobel prize laureate Richard Feynman stated "There is plenty of room at the bottom", going on to elaborate on the possibility of directly manipulating individual atoms. Today, nanoscience is considered a strategically important key technology with high societal relevance and high economic potential in advancing all kinds of areas, for example leading to an enhancement of the human mind, cognition and body, to remedy illnesses, military advancement, better food-production, new machine-body interfaces and better transportation- and communication systems (Roco and Bainbridge 2002; BMBF 2004; Kearnes and Macnaghten 2006; EU 2004). Nanoscience, as one of the most dynamic "new sciences" (Bonaccorsi 2008), has exponential publication growth rates (Braun et al. 1997; Schummer 2004). Figure 1 shows that the number of publications in nanoscience worldwide has risen almost sixfold in the last twelve years (from 9610 to 54236). Unlike astrophysics, nanoscience is a field with high intra-paradigmatic diversity; researchers work in significantly different directions whilst at the same time sharing their basic assumptions and techniques (Bonaccorsi and Vargas2007).

Astrophysics is a science field with relatively clear borders. An identification of astrophysical papers in the SCI with the help of a key-word based search strategy reveals which subjects, journals, in which astrophysical papers are published, are assigned to.[5]

Nearly all publications are assigned to "astronomy and astrophysics" (cf. Fig. 2). There are two main relevant overlaps to other fields, one to "physics, particles and fields" and "multidisciplinary physics". This reflects the importance of (basic) physical science for astrophysics (and vice versa). The second overlap is to some geological sciences such as "multidisciplinary geosciences", "geochemistry and geophysics" and "meteorology and atmospheric sciences". This reflects the interest of Astrophysics in the geological and meteorological nature of celestial objects. The global map of science reinforces the results of Fig. 2; it shows that astrophysics is a relatively isolated science with few links to other fields of science (cf. Fig. 3). The only noteworthy knowledge interdependencies exist with respect to physics (especially particle physics). The overlap and diversity of the other fields is small and the discipline shows a clear profile.

Following Kuhn (1957, 1970), we consider astrophysics to be a paradigmatic science, that is a science with little intra-paradigmatic diversity. Since the observation in 1998 that the expansion in the universe is accelerating, astrophysicists have concentrated their work around the Lambda-CDM Model that can be understood as a paradigmatic standard model of astrophysics. Task uncertainty is low while mutual dependence is high, given high degrees of specialization and large institutional complementarities.

For the success of astrophysicists it is vital that they gain access to telescopes (McCray 2000). In Europe Telescopes are mainly operated by national or supranational organisations (e.g. ESO). In the USA there is a stronger tradition of private sponsorship of telescopes and

[5] A key-word based search strategy to identify articles from a field is more precise than a strategy based on the SCI subject categories because journals are assigned to one or more subject categories without discerning for discrete articles. The subject categorisation in the SSCI (which is comparable to the SCI) is discussed in further detail in Glänzel et al. (1999).

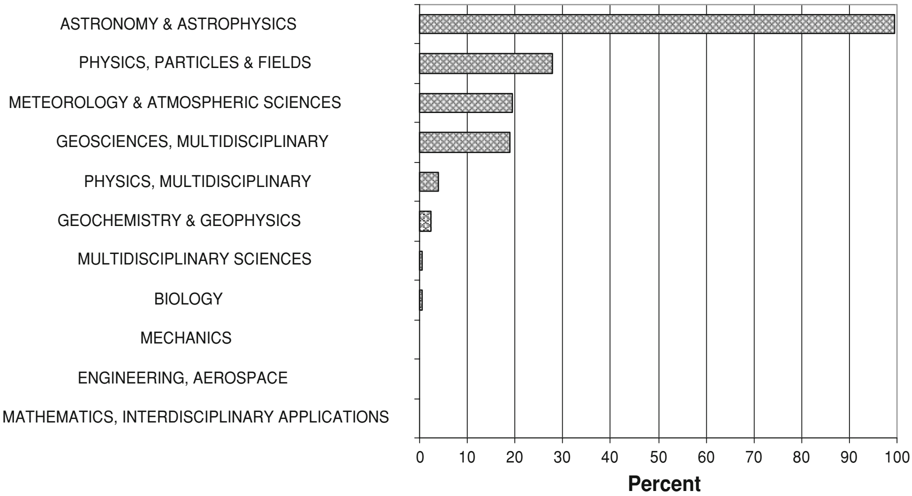

Fig. 2 Publications involving astrophysics according to the SCI-systematic of academic disciplines, in % (*Source*: SCISEARCH (STN), Calculations of the Fraunhofer ISI, multiple codings)

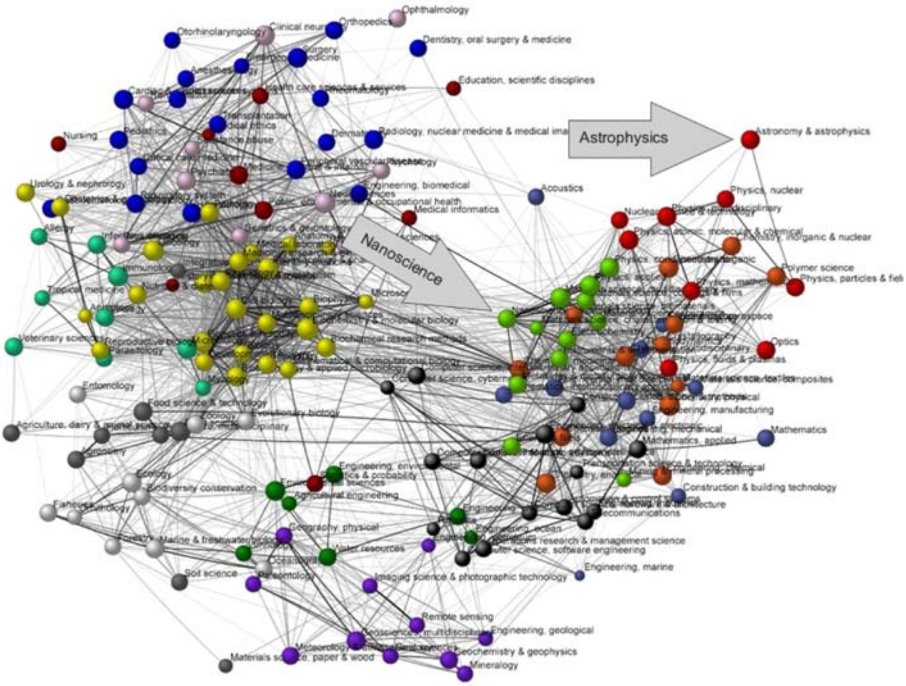

Fig. 3 The positions of astrophysics and nanoscience on the global map of science (Leydesdorff and Rafols 2009)

the access to such private telescopes is often exclusively given to specific scientists (e.g. Keck Observatories) (McCray 2000). Access to non-private national and international telescopes is usually allocated through the peer review of observation proposals.

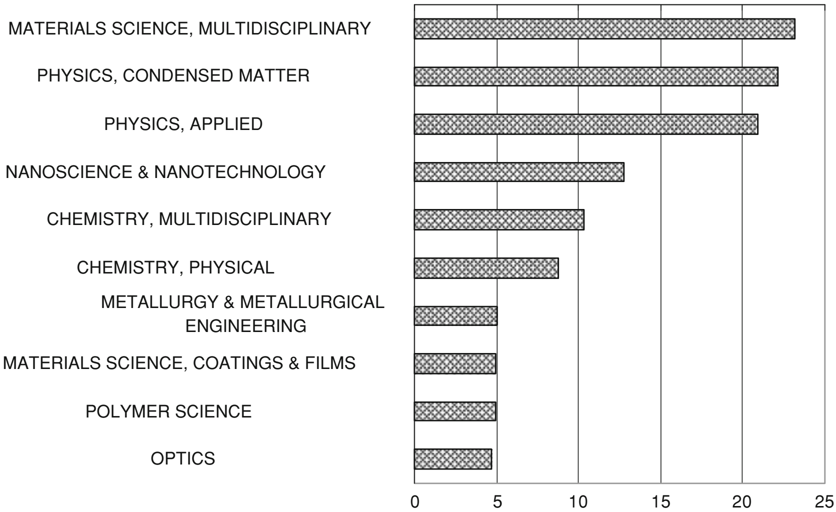

Fig. 4 Publications involving nanoscience according to the SCI-systematic of academic disciplines, in % (*Source*: SCISEARCH (STN), Calculations of the Fraunhofer ISI, multiple codings)

The heterogeneity of disciplines involved in nanoscience mirrors the (potential) areas of application of the field. A detailed analysis of the publications in the field confirms its multidisciplinary character: only about 13% of all publications in the Science Citation Index (SCI) in the field of nanoscience are published in journals classified as specific nanoscience and—technology journals. Figure 4 shows that materials science, physics of condensed matter and applied physics as well as chemistry and physical chemistry all widely report the results of studies in nanoscience.

Leydesdorff and Rafols (2009) produced a "global map of science" by studying the citation relations between the 171 subject categories and the according journals for the whole SCI. The position of the field of nanoscience reflects the heterogeneity of disciplines involved (cf. Fig. 3). The map shows that nanoscience is deeply embedded in a variety of disciplines with links to a multiple of other disciplines. Unlike astrophysics, which sits apart from most other disciplines, with connections to only three subfields of physics, nanoscience is far more enmeshed in the global web of science.

To sum up the results, following Bonaccorsi (2008) and Bonaccorsi and Vargas (2007) we consider nanoscience to be a new science field exhibiting high growth rates, a high degree of divergence of research directions, high task uncertainties and little mutual dependence whilst astrophysics is characterized by little intra-paradigmatic diversity, low task uncertainties and strong mutual dependence and high institutional and cognitive complementarities.

Network structure, network heterogeneity, network resources and strategy

Although there have always been research collaborations in astrophysics, astrophysics has become a highly labour divisive "collective science" since WWII (Fernandez 1998). The average number of authors per paper has reached 3.35 (Newman 2001). Fernandez gives five main reasons for the collective character of astrophysics: the professionalization of science, the stronger pressure of producing papers on a high rate, a value shift towards

Table 2 Average size of research groups and research networks, average duration of collaborations

	Astrophysics	Nanoscience	Significance
Average size of research groups	11.87	15.41	–
Valid cases	31	35	
Average size of research networks	10.74	10.72	–
Valid cases	31	36	
Average duration of collaborations (in years)	10.13	7.89	–
Valid cases	28	30	

*** Significant at 1%-level, ** significant at 5%-level, * significant at 10%-level

team work, a lowering of the costs of communication through new technologies, and a rising complexity of scientific problems. Although these developments can also hold true for other sciences, our thesis is that for astrophysics team work in dense stable research networks is especially productive (H2).

A co-authorship network analysis of astrophysical papers by Newman (2001), shows that the "clustering coefficient", indicating the clique-structure of a network, is relatively high.[6] Collaborations are stable and last a long time. In our data, the average number of years of duration of collaborations is more than 10 years for astrophysics (Table 2).

The size of the research networks of nanoscientists and astrophysicists in our sample is roughly the same, but research groups are bigger in nanoscience and the average duration of collaborations is shorter than in astrophysics (Table 2). Astrophysical networks also show a relatively low diversity in the resources that are exchanged through the networks (Table 3). Collaborations in astrophysics mainly bridge complementary resources between theory and observation skills and help to get access to instruments.

Access to instruments and technical equipment plays an essential role in both nanoscience and astrophysics (Table 3). However, in nanoscience access to technical instruments is not normally formalised but is granted on an individual basis and is often reflected in research collaborations with partners providing materials, specific measurements and/or access to instruments. Table 3 shows the resources accessed through collaboration partners to be much more diverse in nanoscience than in astrophysics. Especially the ability to create/manufacture certain materials and knowledge in specific nanostructures are sought after resources in a collaboration partner in nanoscience. In astrophysics the most important resource of collaboration partners is specific knowledge in theory building and calculations. This reflects the fact that in astrophysics collaborations often occur between astrophysicists specialising in observation and those specialising in theory building (Franke et al. 2006, 52f.).

The fact that research in the field of nanoscience is conducted by multiple academic disciplines does not necessarily mean that the research itself is always conducted in an interdisciplinary manner (Schummer 2004). Disciplines are still a central organisational principle of academic nanoscience research (Heinze 2009); and according to Meyer it "occurs within the established disciplines rather than in an individual interdisciplinary

[6] The clustering coefficient was introduced by Watts and Strogatz (1998) and can be written as follows:

$$Clustering\ Coefficient\ (C) = \frac{3\ \times\ Number\ of\ Triangles\ on\ the\ Graph}{Number\ of\ connected\ Triples\ of\ Vertices}$$

where a "triangle" is a group of three authors, each of whom is connected to both of the others, and a ''connected triple'' is a single author connected to two others.

Table 3 Resources provided by collaboration partners (in %)

	Astrophysics	Nanoscience	Significance
Access to research field	2.8	2.2	
Ability of create/manufacture materials	2.3	20.7	***
Specific skill in measurement	18.2	16.3	–
Specific knowledge in theory building/calculations	34.7	18.7	*
Access to large technical instruments	24.3	16.1	–
Knowledge in subject matter and/or specific structures	16.0	24.1	–
Context of subject matter/Interaction with users/Upgrading	1.7	1.9	–
Valid cases	22	24	

*** Significant at 1%-level, ** significant at 5%-level, * significant at 10%-level

effort" (Meyer 2005, p. 317). However, the wider research networks of research groups are often heterogeneous and span more disciplines than the research networks of astrophysicists for example. In our data we calculated the network heterogeneity using Blau's heterogeneity index (Blau 1977). The index is calculated as follows:

$$H = 1 - \sum_{i=1}^{n} s_i^2,$$

where N is the number of disciplines involved and s_i is the proportion of collaboration partners from this discipline. The index varies between zero and one. Value one represents maximal heterogeneity; i.e. if a lot of researchers from different disciplines comprise the network to a similar scale the value is high. Table 4 shows that nanoscientists have far more heterogeneous networks than astrophysicists, the figures being 0.31 and 0.16 respectively. Overall however, the networks are still mostly dominated by a single discipline. In a similar effort to distinguish the intra- and inter-disciplinary research collaborations of nanoscientists, Leung (2007) found the average intra-disciplinary collaboration in nanoscience to be about 11% whilst the average inter-disciplinary collaboration is about 4%. But nanoscientists do not only cooperate with partners from different disciplinary backgrounds but also with partners from industry. In our sample the average amount of industry ties is 10.4% for nanoscientists. In astrophysics, cooperation with the private sector is virtually irrelevant, only 2.5% of collaborations involve a partner from industry.

Table 4 Disciplinary heterogeneity of networks, average number of disciplines within research groups and proportion of network partners from industry

	Astrophysics	Nanoscience	Significance
Disciplinary heterogeneity of research networks (Blau-Index)	0.16	0.31	*
Valid cases	18	22	
Average no. of disciplines within research groups	1.3	1.9	*
Valid cases	20	20	
Proportion of network partners from industry in %	2.5	10.4	**
Valid cases	25	25	

*** Significant at 1%-level, ** significant at 5%-level, * significant at 10%-level

Table 5 Network strategy: choice of research partners (in %)

		Astrophysics	Nanoscience	Significance
Emergence/path dependence	Agree	54.2	56.5	–
	Somewhat agree/disagree	41.7	43.5	–
	Disagree	4.2	0.0	***
Strategic, based on a limited pool of partners	Agree	45.8	29.2	–
	Somewhat agree/disagree	37.5	50.0	–
	Disagree	16.7	20.8	–
Strategic, based on an open search for partners	Agree	13.0	25.0	–
	Somewhat agree/disagree	26.1	37.5	–
	Disagree	60.9	37.5	–
Valid cases		24	23	

*** Significant at 1%-level, ** significant at 5%-level, * significant at 10%-level

To discern which network strategy is preferred by research groups, the group leaders were asked for their network strategy. A typology of three different network strategies was developed on the basis of the qualitative interviews with research group leaders in 2004 (Wald et al. 2007). Three main types of network behaviour were identified; first the path-dependent emergent network development, which can be characterized by a complete lack of strategy—actors usually meet at conferences, converse and networks develop. As can be expected, this behaviour is the most common method of developing contacts with new collaboration partners. Slightly less common but still important is the strategic search for network partners. Strategic search behaviour can be differentiated into two network strategies: an open search for network partners and a more closed choice from a pool of well-established research partners. Table 5 shows that astrophysicists prefer to rely on a set of known researchers from which they choose partners for specific projects. This can be explained by the role of research networks for the process of gathering telescope observation time. Developing research projects and writing proposals for telescopes is a complex collaborative process. A well-rehearsed research network is needed to perform this task successfully.

Collaboration and exchange with partners from different disciplines are essential components in conducting research in nanoscience (Table 3). Unlike in astrophysics, the social organisation is less cliquish (Newman 2001[7]) and the necessity for boundary-spanning collaboration and an understanding of research in other disciplines is higher (Bonaccorsi 2008). This is reflected in the network strategy of nanoscientists: whilst most network partners are chosen path dependently, a quarter of research groups also state that they strategically search for (hitherto unknown) partners from the community for certain collaborations (Table 5).

On the basis of the description of the field, its characteristics and the research networks in astrophysics, our first hypothesis (H1a) concerning the nature of research in astrophysics can be asserted. The findings can be summed up in three statements:

1. The field of astrophysics is growing slowly; it is almost in a steady state.

[7] Newman (2001) establishes this for the field of “physics of the condensed matter”, one of the sub-disciplines of nanoscience (compare Fig. 4).

2. The field is relatively paradigmatic and not very diverse. Its methods and theories are comparatively standardized. Bringing distant knowledge aspects together is not very important; boundary spanning between diverse academic disciplines is not elementary.
3. Task uncertainty is low and mutual dependence is high such that access to the most sophisticated facilities and highly reputed collaborators is vital.
4. Dense, stable research networks can help gain access to telescopes because well-rehearsed research teams can be expected to be more successful in getting proposals accepted and in gaining research time at high-end telescopes.

From this insight into the functioning of the field of astrophysics we can formulate a more precise hypothesis on the structure of successful collaboration networks in this field: Because of the nature of the field we believe that in astrophysics closed collaboration networks are more productive than networks rich in structural holes (H3).

On the basis of the description of the field, its characteristics and the research networks, our hypothesis (H1b) concerning the nature of research in nanoscience can be asserted. Our findings can be summed up in four statements:

1. The field of nanoscience follows an almost exponential growth path.
2. The field is less paradigmatic and more diverse than for example the field of astrophysics and its methods and theories are less standardized. Therefore it is vital to bring distant knowledge aspects together; boundary spanning is elementary.
3. Task uncertainty is high whilst dependence on particular others is lower than in astrophysics.
4. Open, flexible research networks allow access to diverse knowledge, resources and information allowing for the insight and understanding that are necessary when conducting research in this highly multidisciplinary field.

From this insight into the functioning of the field of nanoscience we can now formulate a more precise hypothesis on the structure of successful collaboration networks in this field: Because of the nature of the field we expect open networks that span boundaries between otherwise unconnected partners and that bring together diverse knowledge and resources to be more productive for research in nanoscience (H2).

Effect of network structure on knowledge production[8]

To test our hypotheses H2, H3 and H4 formulated above, we measure the network constraint in the collaboration networks of the two fields as well as their academic output. The measurement of network constraint allows us to assess whether the research networks of the research groups are concentrated directly or indirectly on a single contact; i.e. it allows us to measure how open or closed research networks really are. The network constraint is calculated as follows:

$$c_{ij} = \sum\nolimits_j \left(p_{ij} + \sum_q p_{iq} p_{qj} \right)^2 \quad \text{for q} \neq \text{i, j},$$

where p_{ij} is the proportion of actor i's network time and energy invested in contact j (Burt 2004, p. 362). Figure 5 shows two exemplary networks from our data, one with a low

[8] All analyses exclude one outlier: a research group in astrophysics with a self-reported output in international conference papers of 300; 11.4 times above the average of 26.3 and 3.3 times above the otherwise reported maximum output of 90 papers.

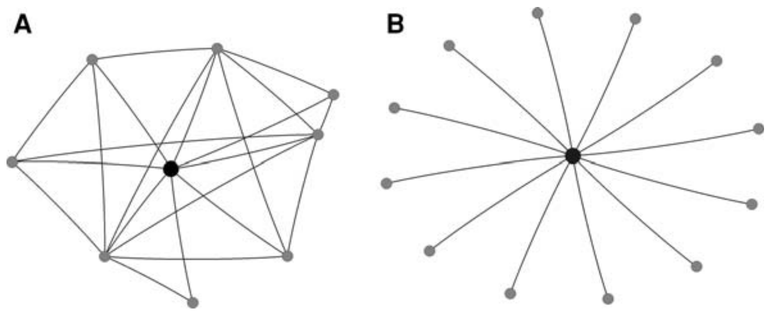

Fig. 5 Two exemplary collaboration networks with high (**a**) and low (**b**) constraint measurements

constraint (bridging structural holes) and one with a high constraint (a closed dense network). Network A is a network of an astrophysical research group with a constraint of 0.406, network B is a network of a nanoscience research group with a constraint of 0.083.[9] The ego research group is marked in black, the alter research groups in grey.

Overall the networks of the astrophysicists are slightly more constrained than the networks of the nanoscientists; however, the difference is very small and not statistically significant (Table 6).

As a measurement of knowledge production, we use the output of international conference papers over a period of two years of our research groups. We chose the output of international conference papers as an indicator for performance because both fields work in an international context; therefore international conference papers can be seen as an indicator for productivity on a high-quality level.[10] Table 7 shows the mean output of international conference papers to be relatively similar in both fields. The range is higher in nanoscience spanning 0 to 200 papers, whereas in astrophysics it ranges from 0 to 90 papers. The output in the field of astrophysics appears to be more evenly distributed, the median being only slightly lower than the mean. In nanoscience output fluctuates more across the field, with 50% of research groups presenting only 13.5 conference papers over the two year period, well below the average of 25 papers.

To test our hypotheses, the interrelation between network constraint and scientific performance was measured conducting a Negative-Binomial Regression Analysis[11]; the

[9] Usually the constraint measure is thought to vary between zero and one, but depending on the size of the network the lower border of the constraint measure will be higher than zero. This is the reason, why the constraint value is higher than zero in our exemplary network B, although there are no crosslinks between the 12 alteri.

[10] We also collected bibliometric data on the number of SCI publications of the research groups between 2004 and 2006 but these data were only available for 49 research groups polled in 2006/07. There is a significant positive correlation between the number of SCI publications and the number of international conference papers of a research group collected by a standardized questionnaire on input and output structure of the research groups (r =0.373**). To allow for a bigger sample size we decided to use the output of international conference papers as the measurement of scientific performance.

[11] The output indicator "number of international conference papers" is a count-variable; therefore only count-data regression models should be applied. First a Poisson-Model was fitted and a test for overdispersion was applied. This test rejected the Poisson-Model on a 0-percent level. A Negative Binomial Model was then computed because the overdispersion-parameters are too high with 0.752 for astrophysics and 0.752 for nanoscience. The dispersion-parameter describes the heteroscedasticity of the model. If the variance is not growing proportional to the expected value of the function, a Negative Binomial Model should be applied, otherwise the significance of the parameters could be overestimated (Hilbe 2007).

Table 6 Network constraint

	Astrophysics	Nanoscience	Significance
Mean	0.28	0.24	–
Median	0.26	0.23	
Std. Err.	0.14	0.08	
Min.	0.06	0.08	
Max.	0.61	0.41	
Valid cases	30	33	

*** Significant at 1%-level, ** significant at 5%-level, * significant at 10%-level

Table 7 Output of international conference papers over a period of two years (self-reported data)

	Astrophysics	Nanoscience	Significance
Mean	26.33	25.24	–
Median	22.50	13.50	
Std. Err.	20.35	37.59	
Min.	0	0	
Max.	90	200	
Valid cases	30	33	

*** Significant at 1%-level, ** significant at 5%-level, * significant at 10%-level

size of research groups and research networks were included as control variables (Table 8). The analysis confirms our hypotheses: network constraint has a negative effect on scientific performance in nanoscience (H2) and a positive effect in astrophysics (H3) (Fig. 6) suggesting that the optimal structural design is indeed context dependent and contingent on characteristics of knowledge production such as task uncertainty and type of mutual dependencies. These differences call for different types of information that need to be exchanged in networks (H4).

Discussion and conclusion

Using data from the second phase of a panel study of research groups and their networks, we have shown that the relationship between network structure and the production of new knowledge is field specific. Our data analysis reveals that this effect varies between scientific fields and is dependent on factors differentiating these fields. Different fields do not generate knowledge in the same way and vary according to the maturity of the field (Bonaccorsi and Vargas 2007; Whitley 2000). Within academic fields different types of networks act as a stimulant for knowledge generation. In a new science such as nanoscience, researchers can be more productive when there are more structural holes in their research networks; in an established field such as astrophysics, the effect is reversed: the

Footnote 11 continued

We also performed a standard OLS-Regression where we logarithmised the dependent variable "number of international conference papers". The direction of the effect of network constraint in the two fields is the same as in the Neg-Bin Model; it is significant at the 10%-level for astrophysics and at the 1%-level for nanoscience.

Table 8 Effect of network constraint on scientific performance

Dependent variable: number of international conference papers of the research group over two years (2003/04 and 2005/06)												
	Astrophysics						Nanoscience					
	Poisson regression			Neg-Bin regression			Poisson regression			Neg-Bin regression		
	Coefficient	Standard error	P > |z|	Coefficient	Standard error	P > |z|	Coefficient	Standard error	P > |z|	Coefficient	Standard error	P > |z|
Constraint	3.52***	0.45	0.000	2.78**	1.34	0.038	−3.42***	0.65	0.000	−4.46*	2.55	0.080
Size of research groups	0.09***	0.01	0.000	0.08*	0.04	0.062	−0.03**	0.01	0.021	−0.06	0.05	0.195
Size of research networks	−0.01*	0.00	0.066	−0.00	0.01	0.758	0.05***	0.00	0.000	0.06***	0.02	0.000
Log-likelihood	−265.14119			−124.74187			−259.43988			−118.34183		
P-Value (LR-Statistic)	0.000			0.001			0.000			0.004		
n	29						31					

The same calculations were performed using the number of SCI publications of the research groups as a dependent variable. The direction of the effect of network constraint in the two fields is the same; however, the results are not statistically significant. Nonetheless we are confident that the effect is real and that the lack of statistical significance is due to the smaller sample size ($n = 49$)

*** Significant at 1%-level, ** significant at 5%-level, * significant at 10%-level

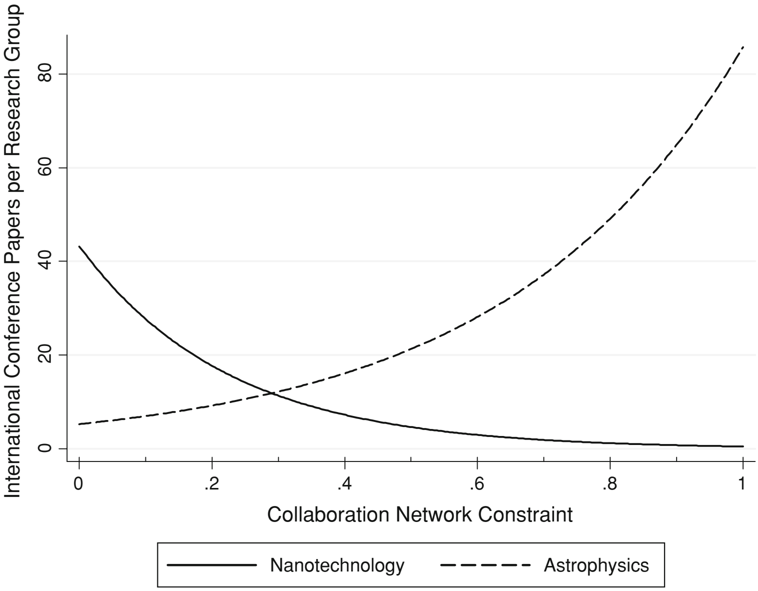

Fig. 6 Effect of network constraint on scientific performance. Predicted values (In order to show the trends of the estimation function the range of values displayed here exceeds the empirical range of network constraints on the axis of abszissae. For astrophysics the maximum network constraint is 0.61, for nanoscience 0.41)

fewer structural holes in the networks, the more productive researchers are. In our study we are able to show that it is not the network structure per se, that determines performance (as Burt suggested) but that this effect is context—and in our case—field specific. The simulation study by Reagans and Zuckerman (2008) on the trade-off between closed networks and brokerage positions in knowledge networks suggests that it is mainly the difference in the valuation of similar knowledge (in our case in astrophysics) versus the valuation of diverse knowledge (in our case in nanoscience) that explains the different implications of structural positions for scientific success. Although the simulation study was criticised for its strict assumptions (Burt 2008), their results are stunningly congruent with our real-world example.

Networks have a facilitative role in the enhancement of scientific performance and the generation of novel ideas but their effect very much depends on a broader set of variables, especially the needs of the individual members of the networks. Brokerage positions provide an advantage, whenever it is important to bring together disparate knowledge and ideas, but when the need for disparate knowledge is saturated, it might be more important to be able to harvest the social capital from closed networks. Where trust plays an important role and where there is need for intense collaboration, brokerage positions might be a disadvantage since the advantages gained from them are small; this position normally implies that one is not embedded in a closely-knit network. The network resources that can be accessed through the different types of network structures vary considerably between open and closed networks. It seems that successful performance is dependent on the availability of necessary resources within the network, and on a fit between the type of task at hand and the existent network structure.

The task at hand, along with the cognitive structures, differs significantly between the fields we analysed in this paper. Astrophysics is paradigmatic and values similar knowledge and therefore benefits from closed collaboration networks whilst nanoscience is an emergent field that values divergent knowledge and researchers therefore benefit from networks rich in structural holes where they can take on a brokerage position. Social factors contribute to these differences, e.g. when networks play a facilitating role to get access to scarce facilities in astrophysics. In nanoscience reputational hierarchies are still in the making and may change abruptly in the fast moving field. Thus a network strategy that maximizes the potential options will be more advantageous.

We are aware of course that network structure is not the only factor influencing scientific performance. In earlier analyses we showed that the proportion of third-party funding and the share of industry ties both have a curvilinear effect on scientific productivity, meaning that a small proportion of third-party funds and/or industry relations can raise productivity, but if the share becomes too big, productivity declines (Jansen et. al. 2007; Jansen et al. 2009). We also tested for a curvilinear relationship between scientific output and network constraint in this analysis but no such curvilinear effect was found for network constraint. However, as our previous results suggest, for nanoscience a network full of structural holes and only industry partners would not be very productive. At the same time, we have not yet found a real life scenario where this is the case and it is not very likely to ever occur. In general, academics always collaborate to some extent with other academics, and in this scenario, social networks with structural holes are productive for nanoscientists but not very productive for astrophysicists.

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