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Individual and Collective Influences on Researchers' Performance in Nanotechnology Networks

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Abstract

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Jelcodes:O33,O38

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Abstract

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Keywords:
Nanotechnology, researchers, network position, interdisciplinarity, European universities of technology

JEL Classification:
O33, O38, O14, P48

1. Introduction

Nanotechnology is one of the key enabling technologies considered as a crucial source of economic growth and employment opportunities (CEC, 2012a). By 2015 about two Million qualified employees will be needed globally in nanotechnology (OECD, 2009). Accordingly, high at the agenda of policy makers are appropriate strategies and tools that can support and stimulate the development and deployment of nanotechnology.

While still being considered an emerging technology nanotechnology has developed into a key enabling technology (CEC, 2009, 2012a). The principle idea underlying nanotechnology emerged more than half a century ago (Feynman, 1959) and its first application dates back about three decades (Binning & Rohrer, 1982). Ever since, there has been a constant flow of new ideas and application areas from nanotechnology (CEC, 2009). Because materials' properties are considerably different on the nano-scale compared to the same material in bulk or macroscopic form, nanotechnology has huge potential in many research areas and opens many fields of applications, (Miyazaki & Islam, 2007): "Nanotechnology holds the promise of leading to the development of smart nano and micro devices and systems and to radical breakthroughs in vital fields such as healthcare, energy, environment and manufacturing." (CEC, 2009, p. 4).

The development and deployment of nanotechnology substantially relies on research done by university researchers, because it is supported by an analytical knowledge base (Asheim, Boschma, & Cooke, 2011). This means that knowledge inputs and outputs are comparably more often codified than in research relying on other types of knowledge bases (Asheim et al., 2011). Scholars' supported by the analytical knowledge base use and create scientific knowledge as well as store and transfer it in codified forms, such as formal models and scientific publications (Asheim et al., 2011). Because of its characteristics nanotechnology forms an important part of the so-called third academic revolution that "… integrates forward and reverse linear models in a programmatic and regulatory framework, synthesizing knowledge, organization and institutions: the … drivers of innovation. The university, thus, becomes an increasingly important platform for societal transformation." (Etzkowitz & Viale, 2010, p. 595).

Researchers' performance relies on factors that are related to the individual level, to the organizational level, to the direct environment in their network, and to overall structure of the network. On the individual level, former findings show that researchers' performance relies on characteristics, such as motivation (Aalbers, Dolfsma, & Koppius, 2013), age, employment status, or their technological profile. On the organizational level factors, such as funding, features of their colleagues and size of the organization, play a crucial role for performance (Cainelli, Maggioni, Uberti, & De Felice, 2010; Carayol & Matt, 2006). Also the structure and the accessibility of the direct environment of researchers' network are important for performance (Aalbers et al., 2013; Carayol & Matt, 2006). Thus, the relationships between individual and organizational level as well as of the direct environment on the one hand side and their influence on academic performance on the other hand side have been analysed before. However, to our knowledge the influence of the structure of the whole network on individual academic performance has so far only been investigated for small networks (Li-chun, Kretschmer, Hanneman, & Liu, 2006).

In this paper, we want to find out what factors influence the output of nanotechnology researchers. This will give us more detailed insight into starting points of how nanotechnology researchers can best be supported and stimulated by university management and research policy. Our analysis does not only focus on the success of the individual researcher but also shows what influence the university as well as the national innovation system they are located at have on their success. We start discussing factors affecting researchers' performance (Section 2.), in particular the network position, the affiliation and the technological profile. To show the influence of the affiliation on researchers' performance we picked researchers employed at the IDEA League Universities by way of example. The IDEA League is a network of European leading universities of science and technology (Section 2.2.3). After setting the theoretical background and the hypotheses in Section 2. we introduce the publication data employed (Section 3.). As a first result we show some feature of the whole nanotechnology network and how the IDEA League universities are located in there using descriptive statistics (Section 4.). With the help of three regression models we explain the performance of nanotechnology researchers worldwide. Moreover, we investigate how being affiliated to one of the five IDEA League universities affect researchers' performance (Section 5.) We round our paper with a short summary of our results, some starting points for university management and research policy, limitations of our approach and further research questions emerging from our results (Section 6.)

2. Performance, Background, Network Position and Technological Profile of Researchers in Nanotechnology

2.1 Researchers' Performance in Nanotechnology

Researchers working at universities of technology have been key contributors to high-quality research and valorisation (Martin, 2012). They have been driving innovation and technological change ever since the later stages of the Industrial Revolution (for details see Section 2.2.3) by particularly contributing to the three roles of universities, i.e. research, teaching and valorisation (e.g. Deiaco, Hughes, & McKelvey, 2012). Researchers have added to the scientific knowledge base, have educated students and have driven technological development by transferring knowledge and expertise to the industry sector. Researchers' performance is mirrored in their output: it comes in different forms as researchers get involved in various scientific and commercialization activities, such as academic entrepreneurship, consultancy, publication of papers and patents (Perkmann et al., 2013). In order to advance their performance researchers collaborate with partners, thereby enabling substantive knowledge sharing between the partners and creating knowledge and innovation (Katz & Martin, 1997).

In our analysis we focus on the core scientific activities, i.e. the research activities that are not explicitly aimed at technology transfer but at knowledge creation and diffusion with the help of the scientific network of nanotechnology researchers. Codified forms of knowledge mainly stemming from academic organizations, particularly by publication data, capture the output of research in nanotechnology for the most part. The reason for this is that nanotechnology is characterized by an analytical knowledge base (Asheim et al., 2011). Consequently, publications essentially mirror technologies supported by an analytical knowledge base, such as nanotechnology, and also reflect related activities well.

2.2 Factors Influencing the Performance of Researchers in Nanotechnology

In the following, we suggest that the performance nanotechnology researchers (Section 2.1) can be particularly explained by their position in the whole nanotechnology network (Section 2.1.1), the affiliation of researchers (Section 2.1.2) as well as their technological discipline and the interdisciplinarity of their research (Section 2.1.3).

2.2.1 Researchers' Positions in Nanotechnology Networks

The position of scholars in the network might govern their performance. The better scholars are connected, the more resources and influence they have. This might lead to more output. Here, we investigate the positions of scholars in a large network, i.e. the worldwide nanotechnology network. Basically, in smaller networks well-positioned scholars are better connected the more links they have. In larger networks, such as the worldwide nanotechnology network, we need to distinguish scholars' position in their direct neighbourhood from their position in the whole network (Li-chun et al., 2006): Larger networks often show highly connected sub-networks that are loosely linked by one or few brokers. These potential gaps between the densely connected sub-networks are called structural holes (Burt, 2000). Structural holes have an advantage and a disadvantage. The disadvantage is that if the brokers would not connect these sub-networks anymore the network would break apart. The advantage is that if two densely connected networks get connected by a broker, researchers in large networks can intensively collaborate in their direct neighbourhood while at the same time having access to collaboration with scholars in other sub-networks as well. Particularly, the knowledge outside their well-connected neighbourhood might lead to innovation of substantial impacts as it might offer new solutions to known problems or new problems to known solutions. So, in a large network to benefit from the direct neighbourhood and from the knowledge in all sub-networks scholars need to be close the scholars in their own neighbourhood as well as via brokers to some researchers in other sub-networks.

Researchers can either be influential in their direct neighbourhood or in the whole network. These two ways of being influential affect the output of researchers in different ways. Firstly, researchers can be influential in their direct environment, thereby benefitting from the specialised knowledge in this part of the network. As this positively influences their ability to produce papers of high quality in this specialised field we suggest:

<u>Hypothesis 1a:</u> The more influential researchers are in their direct network environment the more productive they are.

<u>Hypothesis 1b:</u> The more influential researchers are in their direct network environment the more often their paper are cited.

Secondly, researchers can be influential in the whole nanotechnology network. This is particularly so when they combine close contacts in their direct neighbourhood with good contacts to other sub-networks. For this they need to be rather close to brokers bridging structural holes. By being influential regarding the whole network researchers have access to more interdisciplinary knowledge. This makes it more likely that researchers produce more novel papers and thus we suggest:

<u>Hypothesis 2a:</u> The more central researchers are in the whole network the more productive they are.

<u>Hypothesis 2b:</u> The more central researchers are in the whole network the more often they are cited.

2.2.2 Researchers' Technological Discipline and Interdisciplinarity

The technological discipline conveys the knowledge base and the experiences a scholar relies on. Differences in technological sub-disciplines of nanotechnology research might have a substantial influence on the way researchers transform research inputs into outputs. Different disciplines also go hand in hand with different network structures that best fit their requirements (Jansen, Görtz, & Heidler, 2009): Mature technologies such as astrophysics have a higher productivity when their networks are rather closed and therefore enable efficient knowledge creation and dissemination. On the contrary, emerging technologies such as nanotechnology have a higher productivity if their members are bridging larger cognitive distances, thereby helping to exploit a whole range of emerging technological opportunities. In nanotechnology researchers can explore many research fields and technological applications (Jansen et al., 2009): It is a very diverse technology with an array of potential and actual methods and theories (Miyazaki & Islam, 2007). We control for differences in technological profiles of researchers to capture the differences in the way research is conducted and distributed which might eventually lead to differences in output. We suggest that while nanotechnology as a whole has the characteristics of an emerging technology there are sub-systems which are already rather mature and are characterized by denser network structure.

Researchers with a more interdisciplinary technological profile might publish more and might be cited more often. As could be shown for another key enabling technology, i.e. information and communication technology, interdisciplinarity positively influence research output (Adams & Clemons, 2011). However, a mitigating factor might be that interdisciplinary research has not really begun to exploit its potential. Therefore, the influence of current discoveries stemming from interdisciplinary knowledge flows has still to develop. We suggest that the novelty of interdisciplinary research makes it easier to publish the results. The monodisciplinary character of journals makes it more difficult to publish interdisciplinary results though. As the broad possibilities to solve problems on the nano-level help advancing many other technologies in novel and ground-breaking ways (see Section 2.) we suggest that the total effect of interdisciplinarity on publication output and citation is positive:

<u>Hypothesis 3a:</u> The more interdisciplinary the work of researchers is the more productive they are.

We suggest that interdisciplinary research is cited in more disciplines, therefore scoring higher in terms of citations as well:

<u>Hypothesis 3b:</u> The more interdisciplinary the work of researchers is the more often it is cited.

2.2.3 Researchers’ Affiliation: The IDEA League Universities

Universities, in particular universities of science and technology, have been a driving force of innovation and technological change ever since the later stages of the Industrial Revolution and concur with the founding of many universities of technology. In the first decades of the Industrial Revolution, i.e. in the first half of the 19th century, craftsmen solved technical problems at hand without bothering too much about general principles guiding these solutions (Etzkowitz & Viale, 2010). Yet, ever since the later stages of the Industrial Revolution, i.e. since the second half of the 19th century, academic scholars turned out crucial agents in wide-spanning networks driving innovative industries. One informative example is the German chemical industry that became world-leader because of systematic support by universities. Synthetic dye was developed because German universities did not only provide and develop important knowledge but also trained advanced students in the latest techniques of chemistry (Murmann, 2006). Another instructive example from this period was the success of the Clyde shipbuilding industry in Scotland (Schwerin, 2004). Here, the networks driving innovation and technological change spanned the whole UK and Europe enabling technology transfer between academic scholars and businessmen. “The essential feature of all these overlapping network interactions is that they increased the amount of information exchanged … especially the academics … worked as catalysts.” (Schwerin, 2004, pp. 92f).

In our analysis we thus focus on five leading European universities of technology whose origins date back to the later stages of the Industrial Revolution. The Imperial College London was founded in 1907 (Imperial_College, 2013), Delft University of Technology in 1842 (Baudet, 1991), the Swiss Institute of Technology in Zürich in 1855 (ETH, 2013), the RWTH Aachen University in 1870 (RWTH_Aachen, 2013) and Paris Tech emerged between 1991 and 2007 from joining together twelve Grand Écoles which partly date back to the 19th, some even to 18th century (Paris_Tech, 2013). Their roles in terms of research, education and valorisation have been evolving ever since (Rosenberg & Steinmueller, 2013). However, valorisation has always been crucial to their portfolio (Martin, 2012). Since 1999 the afore-mentioned five leading universities of technology have formed the so-called IDEA League. a network of European leading universities of science and technology (IDEA_League, 2013). At the end of 2012 the

Imperial College left the network (Imperial College, 2013). However, as we analyse data from the time period before we include the Imperial College in our analysis and consider it being part of the IDEA League network.

While the IDEA League universities have a similar background by being universities of science and technology and by belonging to the European Research Area they differ because of their specific national background. The IDEA League universities differ as they belong to different countries and are subject to a variety of national and regional policy measures as well as to different institutional and organisational set-ups. In particular, they belong to different national innovation systems. National innovation systems comprise a set of institutions forming the background in which innovative actors, such as researchers at universities, firms, public and private research organizations but also consumers and policy officials can develop and diffuse new technologies and create knowledge and innovation (Edquist, 2011). As a consequence the incentive structure and the possibilities open to researchers at the IDEA League universities differ. To give an example the institutional set-up of the French innovation system is relatively closed, e.g. a lot of publications take place in the national language to inform national colleagues (Carayol & Matt, 2006).

The IDEA League Universities are similar as they are all situated in Europe and are part of the European Research Area. Therefore, the IDEA League Universities are subject to the European research culture and the European Union (EU) research policy. The Netherlands, Germany, the UK and France are part of the EU and thereby directly subject to EU research policy. Switzerland does so via a bilateral agreement with the EU (Swiss Federal Department of Foreign Affairs, 2012), which has put Switzerland on equal footing with the EU countries for the 7th Framework programme (2007-2013).

The combination of similarities and dissimilarities of the IDEA League universities enables us to show how researchers function in similar ways within nanotechnology or differ and how this might be due to the research environment, i.e. university management and research policy. All five IDEA League Universities stem from countries showing features of open and excellent research system – though in different degrees (CEC, 2012b); only France shows some weaknesses as researchers are underrepresented regarding top 10 percentage of cited scientific papers. This means in particular that IDEA League universities may set tougher standards for recruitment than the average universities. They may also be able to afford better capital equipment or soft infrastructures, resulting in a higher productivity of scientific research. Furthermore, social networks may be multi-levelled – researchers may structure their own personal, social contacts, but then, networks of universities may also play a role in structuring the network.

The openness or closeness of an innovation system and the universities situated within affect the incentives of researchers to globally collaborate. Given the open character of the innovation systems of all five IDEA League universities (CEC, 2012b) we suggest that they collaborate more internationally:

Hypothesis 4: The more open an innovation system, such as that of the IDEA League universities, is the more researchers working in such an innovation system collaborate with international partners.

Researchers collaborating more often globally have access to a much broader pool of knowledge and thereby potentially to the world leaders in their field. This in turn might affect the quantity and quality of their output, particularly of researchers affiliated to the IDEA League universities:

Hypothesis 5a: Researchers affiliated with IDEA League universities are more productive.

Hypothesis 5b: Researchers affiliated with IDEA League universities are more often cited.

Researchers' affiliation also partly influences the network positions of researchers (see Section 2.2.1) in two ways. One, the university management and the research policy within the national innovation systems influence the attitude of researchers regarding their networking. They do so by formal and informal norms as well as by financial and reputational incentives. Two, the ability of researchers to utilize their social network depends crucially on the way their affiliations are connected in the network:

Hypothesis 6: Researchers connected to one of the IDEA League universities are better able to bridge knowledge across the network.

3. Publication Data on Nanotechnology

For our analysis we will employ publication data. This means that our results will mirror mainly the academic research done in nanotechnology. We particularly rely on publication data representing research activities that enhance the scientific knowledge base. As nanotechnology is a research area supported by an analytical knowledge base relying substantially on formal modelling and codification (Asheim et al., 2011), we suggest that our choice of indicators stemming from publication data mirrors output and networks adequately. Moreover, as universities of technologies and namely Imperial College, RWTH Aachen University and Swiss Institute of Technology have successfully combined valorisation with high-quality research (Martin, 2012) we argue that our results based on publication data show the success directly for scientific research and indirectly for valorisation.

Publications are an important output for scientific research, certainly in the academic world (Nelson, 2009). While quantity of output can be measured by the number of publications the quality, i.e. the influence researchers have, can be best captured by the number of citations. In particular, the output of academic scholars and the quality of their work are well-presented by the number of publications and of citations respectively. This is notwithstanding the fact that publication data has limitations (Nelson, 2009).

In the database Web of Science we identified the nanotechnology related sub-set of data from the Web of Science. We followed (for details on the preparation and cleaning of the data see Cunningham & Werker, 2012). In particular we used the query design developed by Porter, Youtie, Shapira, and Schoeneck (2008), in consultation with nanotechnology experts. Our resulting dataset covers the time period from 2008 until 2012 and includes 700 thousand individual researchers. Within this dataset we identified the publications of all researchers affiliated with one of the IDEA League universities. In order to do so we employed a thorough routine of cleaning addresses which are sometimes ambiguous (see Appendix A). The subject categories contributing to nanotechnology research cover a wide array of research fields in engineering and physics (see Appendix B.). The largest field is ‘all others’ with 36.3% This already indicates that many researchers working on nanotechnology do a lot of other research as well (Cunningham et al., 2013). The second largest group with 18.1% is ‘materials science’ together with materials science, multidisciplinary’ which not surprisingly forms the core of the nanotechnology network (Cunningham et al., 2013). ‘Chemistry’ together with ‘Chemistry, Physical’ and ‘Chemistry, Multidisciplinary’ (20.7%) and ‘Physics’ together with ‘Physics, Applied’ (15.5%) also play a big role in nanotechnology. ‘Science and Technology, Other Topics’ (5.8%) as well as ‘Polymer Science’ (3.4%) are of lesser importance.

4. IDEA League Universities in Global Nanotechnology Networks

Researchers at the IDEA League universities working on nanotechnology have made constant contributions to the field, well-excess of a hundred articles per year for each university. In Table 1 you find the number of publications on nanotechnology worldwide and for the five IDEA League universities for the time period 2008 until 2012. The amalgamated University of Paris universities are by far the largest contributor.

	2008	2009	2010	2011	2012	Total
Worldwide	73,927	81,831	89,001	103,035	75,663	423,457
Delft University of Technology	161	214	216	246	161	998
Imperial College London	230	242	308	328	247	1,355
Paris Tech	683	679	714	749	564	3,389
RWTH Aachen University	133	161	170	196	150	810
Swiss Institute of Technology Zürich	305	314	377	374	273	1,643

Table 1: Number of Publications on Nanotechnology Worldwide and Stemming from the IDEA League Universities.

Researchers at the five universities working on nanotechnology performed differently regarding the following output measures, with a comparator to the average university in global network (see Table 2). In order to measure research quality we examine citations per paper, a measure of research quality. Moreover, we looked into co-authorship and papers per unique author, two indicators commonly associated with research productivity. In addition, we measure both internal collaboration, as well as international collaboration. All papers which do not emerge from internal collaboration do so from external collaboration. A fraction of those papers with external collaboration are also international. Finally, we include the percentage of researchers connected to the largest component of the social network (Hannemann & Riddle, 2005). In cases where there are isolates or non-connected sub-groups the information about the researchers who are connected to the largest set of actors who are all connected gives some indication where they are located in the overall network.

	Citations per paper	co-authors per paper	Papers per unique author	% internal collaboration	% international collaboration	% largest component
Comparator = average of universities in the global network	4.11	4.97	4.35	47%	24%	44%
Delft University of Technology	6.47	6.10	1.13	23%	50%	57%
Imperial College London	6.98	7.98	0.93	22%	62%	51%
Paris Tech	7.91	5.05	1.00	15%	51%	54%
RWTH Aachen University	7.25	5.25	1.06	22%	49%	48%
Swiss Institute of Technology Zürich	6.38	6.50	1.06	33%	53%	49%

Table 2: Output Measures of Papers Published by IDEA League Authors and Comparators on the Average University in the Global Network.

The results show that papers with IDEA League (co-)authorship are far more cited than average. They also incorporate more collaborators than most. A surprising finding is that authors appear to publish fewer papers. With this naïve measure – papers per unique author – comes several sources of ambiguity. IDEA League (co-)authors may invest in fewer, higher quality papers. One possible explanation is that European universities tend include a higher proportion of junior staff, not yet well-published. Moreover, IDEA League researchers may be publishing more broadly in non-nanotechnology fields.

Researchers from the IDEA League universities are very active external collaborators, much more than average. More than 70% of these external collaborations occur internationally. Again, this is much higher than average. Thus, we can accept hypothesis 4, suggesting that researchers affiliated with one of the IDEA League universities collaborate more internationally. A final note is that the IDEA League university researchers are better networked socially than average. More than half the researchers are connected to the "large component" in the graph. As could be shown this is a major determinant of whether researchers can uptake new nanotechnology knowledge (Cunningham et al., 2013).

Researchers working on nanotechnology at the IDEA League universities occupy an interesting and intermediate position in the network. They are neither very centrally located, nor at the far periphery of the network. We use the concepts of geodesic distance and radius to show this. Geodesic distance is the length of the shortest path from one researcher to another (Hannemann & Riddle, 2005). To calculate the eccentricity of a researcher you need to look at all geodesic distances of this particular researcher connecting him/her to all other researchers in the network and to pick the largest geodesic distance (Tamas & Pazmany, 2013). In other words, the eccentricity of a researcher is the longest path with which s/he is connected to another one in the network. The center of the network is that actor or those actors with the lowest eccentricity. The radius of a researcher is the geodesic distance from that researcher to the center. Thus, the radius gives us the possibility to determine the position of a researcher in the network in terms of center or periphery. The central researcher or the central researchers in the network have a radius of 0. All other researchers' radius is related to this. The researchers with the biggest radius form the periphery of the network.

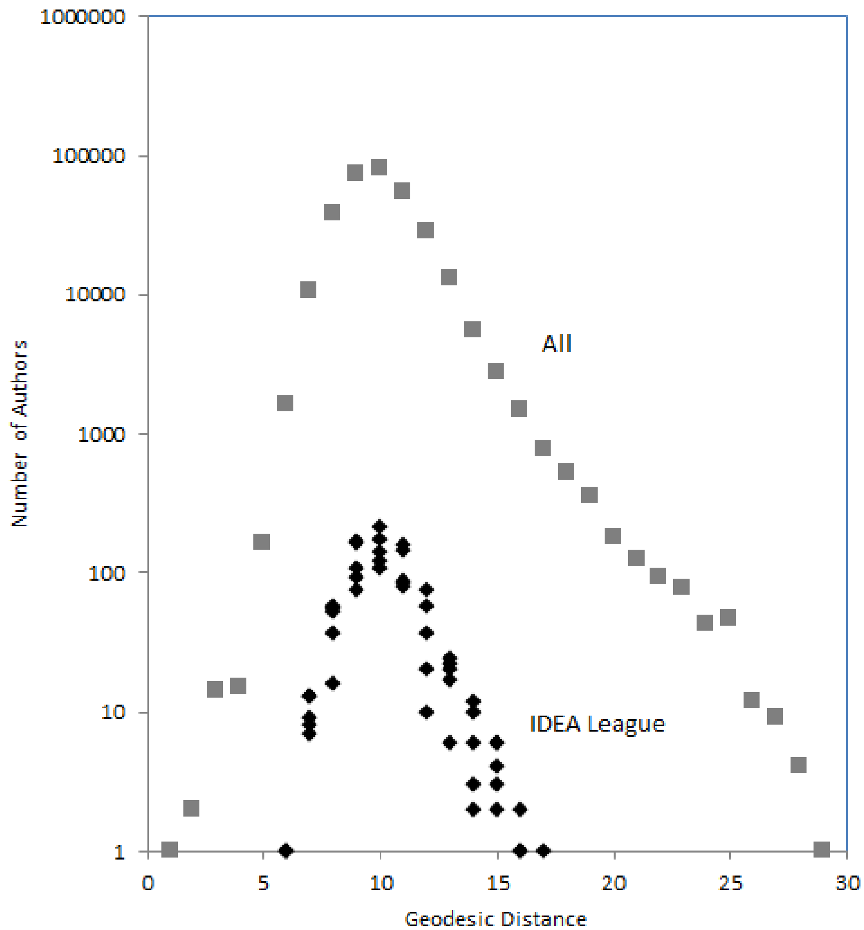

Figure 1: The Distribution of Geodesic Distances of Researchers Working at the IDEA League Universities and of Researchers in the Whole Nanotechnology Network.

IDEA League researchers are similar as they occupy a “ring” at about 10 hops from the center of the network. Figure 1 shows the total number of authors at each geodesic distance in the network. The characteristics of the network as a whole are shown in grey, and the characteristics of the five IDEA League universities are shown in black. Geodesic distances vary from zero to twenty-nine in the network. These distances are only for the largest component of the graph – many researchers are disconnected from this hub. The observed distances do not readily match well-established probability distributions. Nor is there much guiding theory describing what distributions should be expected of the data. Particularly noteworthy is the high skew in the data, coupled with a low variance. However, as could be shown elsewhere new nanotechnology knowledge emerges from the periphery of the network (Cunningham et al., 2013). An intermediate position, like that of the IDEA League universities, may be a fruitful location for large, general purpose research organizations. It may well be that specialized nanotechnology research organizations exist at the periphery of this network – at twenty hops or beyond.

5. Factors Influencing the Performance of Researchers in Nanotechnology

In the following we introduce three models explaining the performance of nanotechnology researchers (Section 5.1). Explanatory factors discussed in detail in Section 5.2 include network position, background and technological profiles of researchers.

5.1 Models on the Performance of Nanotechnology Researchers

In Section 5.1.1., we formulate three models examining the relationship between the performance of nanotechnology researchers, their position, their technological profile and their affiliation. Then, we give an overview of the results of the three models (Section 5.1.2). For a detailed discussion of the results see Section 5.2.

5.1.1 Model Equations and Variables

The three models employed in the following are standard multiple linear regression models as explained below.

1) $Y_i = b_0+b_{ij}X_{ij}+\mathcal{N}(0,\sigma_i^2)$,
   $i = (1..5),\ j=(1..11)$

Our models iterate the i's across the three dependent variables and the j's across the eleven independent variables. Normally distributed errors are added to the regression outputs as is standard. There are potentially three distinct sources of noise corresponding to the three modelled dependent variables (see equations 2 and 3). The dependent and independent variables are indexed by the subscripts i and j. In Table 3 we list these variables. Variables as noted are transformed using the logarithm. Variables where zeros are possible are first standardized by adding a one before the logarithm to avoid an undefined error. Where noted the variables are logical variables and their respective scoring for zero and one are noted. Where noted for disciplinarity, the variables are categorical and sum to one hundred percentage across all subject categories.

Variable	Variable Name	Link Function, Variable Type
Y_1	Citation	+1, log
Y_2	Publication	Log
Y_3	Fractionated Publication	Log
X_1	Degree Centrality	Log
X_2	Radius	None, Integer
X_3	Connected to the largest component	None, Logical (disconnected = 0, connected =1)
X_4	Residing in one of the IDEA League universities	None, Logical (no=0, yes=1)
X_5	Enhanced Network Utilization (X_2 X_4)	None, Integer
X_6	Subject Cat 1: Chemistry	Categorical, Ratio
X_7	Subject Cat 2: Physics	Categorical, Ratio
X_8	Subject Cat 3: Materials Science	Categorical, Ratio
X_9	Subject Cat 4: Polymer Science	Categorical, Ratio
X_{10}	Subject Cat 5: Chemistry, Multidisciplinary	Categorical, Ratio
X_{11}	Interdisciplinarity	None, Ratio

Table 3: List of Variables

The three dependent variables modelled include earned citation to measure quality, total publications to measure scientific output, and fractionated publications to measure productivity. In particular, we use the number of publications as well as the number of citations per author. That means that we measure the success of researchers in terms of output and in particular in terms of publications. The reasons for this choice of indicators are threefold: One, publications in scientific journals guarantee a certain minimum level of quality as they are peer reviewed (Hoekman, Frenken, & Oort, 2008). Two, the data on publication provides detailed information about author, location, kind of research etc. This holds particularly for the publication data we use as all the publications are registered in the Social Citation Index of the Web of Science. Therefore, the (minimum) quality and the quantity of academic output can be reasonably captured by the number of publications in a specific period (Nelson, 2009). Three, the quality of academic output can be measured by the number of citations a publication gets, as these show the influence a particular paper has on the community (Larsen, 2008; Nelson, 2009). Publication output is often fractionated in scientometrics studies (e.g. Cunningham & Werker, 2012). This fractionated count is intended to better represent the proportional effort spent in publication when there are multiple authors. A simple fractionation procedure is used here – papers are divided equally in credit among all co-authors. Note that fractionated publication is completely determined by total publication count as well as average number of co-authors.

There are three groups of independent variables representing, one, the network position of researchers (Section 2.2.1), two, technological discipline and interdisciplinarity of researchers (Section 2.2.2), and three, the affiliation (Section 2.2.3). In the first group of independent variables, in order to show the influence of researchers' network position on their performance, we use three indicators. In particular, we calculate degree centrality, radius and connectivity to the largest component. Degree centrality counts the number of direct connections of a node, i.e. here a researcher (Hannemann & Riddle, 2005): "... (N)odes with higher degree or more connections, in a sense, are more central to the structure and tend to have a greater capacity to influence others. ... a measure of how influential … the node may be" (Li-chun et al., 2006, pp. 1602ff). "Degree centrality .. identifies actors who are locally influential." (Li-chun et al., 2006, p. 1603). In contrast, radius and connectivity to the largest component show how researchers are situated in the overall structure of the network. Radius indicates how the researchers are related to the centre or periphery of the network's most central actors (see also Section 4.) So does the indicator showing whether or not researchers connect to the largest component of the network (see also Section 4.). When a researcher is connected, this variable is scored as 1, when s/he is disconnected; this variable is scored as 0.

In the second group of independent variables, to account for the influence of technological discipline and interdisciplinarity on performance, we use the coding of the journals in which the respective author publishes. To control for the disciplinary differences (see Section 2.2.2) in publication and citation, we add the percentage of research conducted in five major subject categories of nanotechnology research, i.e. Chemistry, Physics, Materials Science, Polymer Science and Multidisciplinary Chemistry. A sixth category of all others is included, making the sum of research sum to 100%. The sixth category of all others is subsumed in the regression coefficient.

To account for the interdisciplinarity of the work of each researcher we calculate the disciplinary profile of each of them on five subject categories and the "all others" category. The calculation uses an information theory measure – the resultant value of interdisciplinarity ranges from 0.000 (monodisciplinary) to 10.756 (completely interdisciplinary in all six categories).

In the third group of independent variables are the two variables related to affiliation. One, we use the variable indicating whether researchers reside in one of the IDEA League universities X_4 and, two, an interaction term calculated as (X_4 x X_2), with X_2 being the radius. The interaction term reflects hypothesis 6 suggesting that well-positioned organizations, such as the IDEA League universities, endow their researchers with enhanced mechanisms for social access and communication. We thereby suggest that the ability of a researcher to utilize their social network was itself determined by their research affiliation.

The ability to utilize social contacts and translate these contacts into productive output is a quantity to be estimated in the model. Specifically in the regression model the beta (b_3) translates the radius of the social researcher into enhanced productive output – all other variables considered. There are three such betas, one for each of the modelled dependent variables. Suppose in turn that this random variable could be further predicted or specified. Specifically, the social utilization of individual researchers may have an incremental bonus (c_{1i}) directly attributable to residing in one of the five IDEA League universities (variable X_4). The relationship is noisy, potentially with distinct sources of noise for each productive output. This noise is introduced with three random variables with differing variances (k = 1…3).

2) $b_{i3} = c_0 + c_{1i}X_4 + \mathcal{N}(0,\sigma_k^2)$, k = (1..4)

This model is a hierarchical linear regression. A full hierarchical linear regression would substitute the beta from equation 2 into the regression specification of equation 1. Our purpose in this model is to test whether more complex hierarchical models of this character are in fact needed. We begin with the following simple, reduced model.

3) $Y_i = b_0 + b_{ij}X_{ij} + c_{0i}X_3 + c_{1i}X_2X_4 + \mathcal{N}(0,\sigma_i^2)$,
$i = (1..4), j=(1,2,4,5)$

The model includes most of the complexity of the full hierarchical regression. It does simplify the noise structure of the model. Specifically, the interaction between the noise of the betas and the regression variables is not being specified or tested. A merit of this specification is that it does examine and test the hypothesis 4 that IDEA League researchers are able to achieve an enhanced utilization of their social network. The resultant interaction term is reflected by the multiplied variables X_2X_4.

5.1.2 Overview of Results of the Models

In Table 4 you find an overview of the results of the models discussed in Section 5.1.1. These results are discussed in more detail in Section 5.2. The correlation between the dependent variables suggests that they are partial, incomplete, but yet cohesive measures of scientific success (see Appendix D).

All models are reported with betas, then standard errors in parentheses, then the significance noted with asterisks. All models and coefficients are significant with p and F tests < 0.001. There remains some unexplained heterogeneity in the models though. The R-squared is 0.299 for Model 1 (explaining citation), 0.501 for Model 2 (explaining publication), and 0.313 for Model 3 (explaining fractionated publication) Full regression diagnostics are provided in Appendix E.

	Model 1 Citation	Model 2 Publication	Model 3 Fractionated Publication
Constant	0.967 (0.00260) ***	0.0406 (0.00101) ***	-1.607 (0.00189) ***
Degree Centrality	0.591 (0.00263) ***	0.506 (0.00151) ***	0.546 (0.00192) ***
Radius	- 0.0962 (0.00123) ***	- 0.0446 (0.000875) ***	-0.0351 (0.000896) ***
Connectivity	8.648 (0.0288) ***	7.0070 (0.0160) ***	7.471 (0.0210) ***
IDEA League	0.350 (0.0228) ***	0.00329 (0.0128)	-0.0736 (0.0167) ***
IDEA League x Radius	-0.00127 (0.00229)	0.000596 (0.00175)	0.00383 (0.00228)
Subject Cat 1: Chemistry	-0.371 (0.00543) ***	-0.168 (0.00285) ***	-0.0905 (0.00396) ***
Subject Cat 2: Physics	-0.551 (0.00584) ***	-0.0863 (0.00307) ***	-0.0517 (0.00426) ***
Subject Cat 3: Materials Science	-1.254 (0.00786) ***	-0.504 (0.00412) ***	-0.294 (0.00573) ***
Subject Cat 4: Polymer Science	-0.405 (0.00814) ***	-0.118 (0.00428) ***	0.0174 (0.00594) **
Subject Cat 5: Chemistry, Multidisciplinary	-0.0465 (0.00920) ***	-0.0644 (0.00483) ***	0.0672 (0.00670) ***
Interdisciplinarity	0.868 (0.00368) ***	0.628 (0.00193) ***	0.407 (0.00268) ***

* significant at $p < 0.05$, ** significant at $p < 0.01$, *** significant at $p < 0.001$

Table 4: Results of Models 1, 2 and 3

5.2 Discussion of the Results

In the following section we analyze the relationship between the performances of nanotechnology researchers in terms of citation, publication and fractionated publication on the one hand side and a number of explanatory factors on the other hand side. These explanatory factors can be subsumed under the researchers' positions in the network (Section 5.2.1), their technological discipline and interdisciplinarity (Section 5.2.2) and their affiliation (Section 5.2.3). Specifically we discuss the hypotheses developed in Section 2.2.

5.2.1 Researchers Positions in Nanotechnology Networks

The three variables indicating the position of scholars in their local environment and in their overall network are all significant at the 1% level, thereby supporting hypotheses 1a, 1b, 2a and 2b (Section 2.2.1). Degree centrality reflecting the researchers' influence in their local environment plays a strong role in determining scientific output. In all cases the association between degree centrality and output in terms of publication output and citation is positive, i.e. we can accept hypotheses 1a and 1b. Because this is a log-log model, this coefficient is interpretable as an elasticity coefficient. Radius also plays a significant role, though with a negative sign. Researchers with a high radius, i.e. farer away from the centre of the network, are less productive in terms of publication and fractionated publication and are poorly cited. Conversely, the core actors around the centre are highly productive and well-cited. As a final note, connectivity with the social network is a very strong contributor in determining scientific output as well. Results both on radius and on connectivity to the largest component support hypotheses 2a and 2b suggesting that more central scholars are more productive and better cited.

5.2.2 Researchers Technological Discipline and Interdisciplinarity

Here, we investigate the influence of technological discipline and interdisciplinarity on the performance of nanotechnology researchers. The disciplinary variables are in the first place control variables, i.e. they make sure that characteristics of the specific discipline do not influence the results of the models. When comparing citations and publications in the five subject categories with the "all others" the five subject categories show comparably fewer citations and comparably fewer publications than the "all other" category (see Appendix C). Striking is the very strong role of interdisciplinarity plays – it enhances both publication and citation. So, both hypotheses 3a and 3b are supported by our results. Researchers working more interdisciplinary are more productive both in terms of publication and fractionated publication. Moreover, they are considerably more cited. This is in line with findings in Cunningham et al. (2013). Interdisciplinarity of researchers' work seems to bridge different part of the network, connecting sub-systems and various disciplines, thereby producing cutting-edge novelty in nanotechnology.

5.2. Researchers' Affiliation

In this section we examine the influence of the institutional and organizational background on the performance of researchers, particularly showing the influence of being affiliated with one of the IDEA League universities. The logic in exploring this is that if the social network of researchers is a prominent determinant of scientific output, and then their research affiliation should also be significant.

Researchers located at one of the IDEA League universities play no appreciable role in the quality of fit for the models. This is not surprising given the comparatively few publications originating from these universities as compared with the whole. Nonetheless the universities do show some significant associations with scientific productivity. IDEA League researchers are associated with nearly a 50% bonus in earned citations (this is the exponent of the coefficient 0.395 in model 1), thereby supporting Hypothesis 5b. Researchers from IDEA League universities are associated with a small, but statistically insignificant advantage in publication output. However, they show a reduction in the number of fractionated publications, thereby rejecting Hypothesis 5a. This is more than attributable by the fact that these universities have significantly larger numbers of authors per paper (see for this and the following see Section 4). Recall earlier findings that researchers residing at the IDEA League were more externally oriented, and more consistently involved in international collaboration than the average researchers. This is consistent with seeking a slightly higher number of authors per paper. IDEA

League researchers are effectively able to operate at a higher radius in the social network than other researchers, without subsequent losses of productivity. This can be seen by comparing the intercept and slope of the IDEA League variables in model 3, effectively a positive offset in favour of IDEA League participants. Furthermore, IDEA League researchers are better able at the margins to manage the social isolation of a high radius, as evidenced by the slope of the interaction term in model 3. In addition, hypothesis 6 is rejected as the interaction term (IDEA League x radius) is not significant for any of the output measures.

6. Conclusions

With this paper, we are able to shed more light on how individual performance of researchers doing nanotechnology research is affected by their position in the nanotechnology network, by their technological profile and by their affiliation, i.e. their institutional and organizational background. For all researchers in the nanotechnology network we find the following: One, researchers better connected in their direct environment and in the overall structure of the network perform better (Section 5.2.1). Two, interdisciplinarity of researchers' work is a crucial driver of performance (Section 5.2.2). Putting one and two together indicate that interdisciplinary work of locally and globally well-connected researchers pushes the frontier of technological knowledge by providing novel solutions to open questions in the researchers' own sub-network, and even more so, by providing well-known solutions to problems from other sub-networks. Three, this particularly holds for general purposes research organizations, such as the IDEA League universities, that occupy an interesting intermediate position in the overall network. Researchers affiliated to them are neither very central in the network nor very close to the periphery (Section 4.). This seems to be a fruitful location for this kind of organization: Researchers affiliated to one of the IDEA League universities are substantially more often cited and link larger and more international communities of researchers (for this and the following Section 5.2.3). They are slightly less productive in terms of publication output though. We suggest that this has mostly to do with the fact, that in contrast to other parts of the world, in Europe the contributions of PhD students and junior staff members is acknowledged by making them co-author.

From our results follow some starting points for university management and research policy. In order to push the technological frontier of nanotechnology, both management and policy should stimulate interdisciplinarity of researchers' work by equally supporting their connectivity to their direct local environment in the network and via brokers to scholars in other sub-networks. For researchers of general purposes organizations, such as the IDEA League universities, management and policy should support their mediating role by enabling to connect even larger and more diverse communities.

There are a number of limitations of our results which suggest further research questions and approaches: First of all, as we analyse publication data our results are biased towards academic research in nanotechnology networks. As nanotechnology strongly relies on an analytical knowledge base and thereby on university research (Asheim et al., 2011) we suggest that our data cover a substantial part of nanotechnology research. In order to include the work of researchers contributing to technological applications of nanotechnology, in particular in the industry sector, we would have to employ other measures such as patent data though (Nelson, 2009). Second, we used citations as a quality measure which is the common way of interpreting them (Nelson, 2009). However, our results might partly also cover seniority of researcher as former analysis show that more senior researchers are usually also more often cited (Cainelli et al., 2010). Adding a measure of seniority to the analysis would help this but proved to be very difficult for our exercise. Third, we did not correct the publication data for impact factor of the journal. While there might be good reasons for doing so, we feel that knowledge published in lower impact journals is nevertheless widely read though not always acknowledged in citing the respective papers. The reason is that there is a citation bias towards heavily cited papers. These papers use to serve as signals to which kind of literature a paper belongs. Fourth, we only looked into the characteristics of one particular group of research organizations, i.e. five leading European university of technology, to analyse the influence of the kind of organization and of the kind of innovation system. We found that being affiliated to those universities had crucial influence on the performance of researchers. These results indicate that it would be interesting to investigate this topic more systematically. This could be done by classifying the various research organizations into categories and by including the systemic differences of the national innovation systems research organizations are located in. We suggest that all four aspects covered above are worthwhile another paper.

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Appendix A: Cleaning of Addresses

We performed an extensive cleaning of institutional addresses, resulting in an estimated 99.4% correct identification of either city and country, or city, province or country. This is performed using a trigram matching algorithm and conservative criteria for finding matches. We use a Jaccard coefficient of 0.60. In the case of the IDEA League universities, a thesaurus of over 400 entries is created, and a mapping produced. In every instance the less frequent entries are recast to more frequently occurring usages in the data.

A unique key for each author is then made as follows

[city][last_name][first_name] OR

[city][last_name][first_initial]

The choice of unique key is dependent upon the last name. A short list of common last names are created. Authors with names on the list use the fully disambiguated first name.

Appendix B:

Rank	Field	Percentage
1	All others	36.3
2	Chemistry	13.3
3	Materials Science	12.3
4	Physics	11.1
5	Materials Science, Multidisciplinary	5.8
6	Science and Technology – Other Topics	5.8
7	Physics, Applied	4.4
8	Chemistry, Physical	3.7
9	Chemistry, Multidisciplinary	3.7
10	Polymer Science	3.4

Table B1: Subject Categories Captured by the Nanotechnology Query

Appendix C:

Number	Subject Category	Citation	Publication
1	Chemistry	fewer	fewer
2	Physics	fewer	fewer
3	Materials Science	fewer	fewer
4	Polymer Science	fewer	fewer
5	Chemistry, Multidisciplinary	fewer	fewer
n/a	All others	greater	greater

Table C1: Comparing the Major Subject Categories in Nanotechnology

Appendix D:

The independent variables are positively correlated. As fractionated publication is calculated with the help of publication the high correlation coefficient is not at all surprising. Moreover, it is intuitively reasonable that the more researchers publish the more they are cited.

	Citation	Publication	Fractionated Publications
Citation	1.000		
Publication	0.708	1.000	
Fractionated Publication	0.566	0.876	1.000

Table D1: Correlation of Dependent Variables

Appendix E: Diagnostics of the Three Models

Table E1: Diagnostics of Model 1 (Citation)

Regression Statistics	
Multiple R	0.547
R Square	0.299
Adjusted R Square	0.299
Standard Error	1.127
Observations	701602

ANOVA

	df	SS	MS	F	Significance F
Regression	11	379530.988	34502.817	27181.611	0.000
Residual	701590	890559.113	1.269		
Total	701601	1270090.102			

	Coefficients	Standard Error	t-Stat	P-value	Lower 95%	Higher 95%
Intercept	0.967	0.003	372.850	0.000	0.962	0.972
Degree	0.591	0.003	224.688	0.000	0.586	0.596
Distance	-0.096	0.001	-78.245	0.000	-0.099	-0.094
Connected	8.648	0.029	300.203	0.000	8.591	8.704
Idea	0.350	0.023	15.325	0.000	0.306	0.395
Social	-0.001	0.003	-0.406	0.685	-0.007	0.005
sc1	-0.371	0.005	-68.234	0.000	-0.381	-0.360
sc2	-0.551	0.006	-94.302	0.000	-0.563	-0.540
sc3	-1.254	0.008	-159.588	0.000	-1.269	-1.238
sc4	-0.405	0.008	-49.671	0.000	-0.420	-0.389
sc5	-0.047	0.009	-5.061	0.000	-0.065	-0.029
Id	-0.868	0.004	-235.784	0.000	-0.875	-0.861

Table E2: Diagnostics of Model 2 (Publication)

Regression Statistics	
Multiple R	0.708
R Square	0.501
Adjusted R Square	0.501
Standard Error	0.591
Observations	701602

ANOVA

	df	SS	MS	F	Significance F
Regression	11	246120.779	22374.616	63972.688	0
Residuals	701590	245382.951	0.350		
Total	701601	491503.729			

	Coefficients	Standard Error	t-Stat	P-value	Lower 95%	Higher 95%
Intercept	0.041	0.001	29.839	0.000	0.038	0.043
Degree	0.506	0.001	366.305	0.000	0.503	0.508
Distance	-0.045	0.001	-69.054	0.000	-0.046	-0.043
Connected	7.070	0.015	467.554	0.000	7.040	7.099
Idea	0.003	0.012	0.274	0.784	-0.020	0.027
Social	0.001	0.002	0.364	0.716	-0.003	0.004
sc1	-0.168	0.003	-58.769	0.000	-0.173	-0.162
sc2	-0.086	0.003	-28.126	0.000	-0.092	-0.080
sc3	-0.504	0.004	-122.258	0.000	-0.512	-0.496
sc4	-0.118	0.004	-27.608	0.000	-0.126	-0.110
sc5	-0.064	0.005	-13.342	0.000	-0.074	-0.055
Id	-0.628	0.002	-324.908	0.000	-0.631	-0.624

Table E3: Diagnostics of Model 3 (Fractionated Publications)

Regression Statistics	
Multiple R	0.559
R Square	0.313
Adjusted R Square	0.313
Standard Error	0.821
Observations	701602

ANOVA

	df	SS	MS	F	Significance F
Regression	11	215581.5425	19598.32204	29047.65324	0
Residual	701590	473359.6428	0.674695538		
Total	701601	688941.1853			

	Coefficients	Standard Error	t-Stat	P-value	Lower 95%	Higher 95%
Intercept	-1.6075	0.0019	-849.8004	0.0000	-1.6112	-1.6038
Degree	0.5462	0.0019	284.9095	0.0000	0.5425	0.5500
Distance	-0.0351	0.0009	-39.1404	0.0000	-0.0368	-0.0333
Connected	7.4706	0.0210	355.7277	0.0000	7.4295	7.5118
Idea	-0.0736	0.0167	-4.4152	0.0000	-0.1063	-0.0409
Social	0.0038	0.0023	1.6819	0.0926	-0.0006	0.0083
sc1	-0.0905	0.0040	-22.8687	0.0000	-0.0983	-0.0828
sc2	-0.0517	0.0043	-12.1257	0.0000	-0.0600	-0.0433
sc3	-0.2937	0.0057	-51.2827	0.0000	-0.3049	-0.2824
sc4	0.0174	0.0059	2.9268	0.0034	0.0057	0.0290
sc5	0.0672	0.0067	10.0299	0.0000	0.0541	0.0804
Id	-0.4069	0.0027	-151.6501	0.0000	-0.4122	-0.4017