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Preferential Attachment and Pattern Formation in R&D Networks—Plausible explanation or just a widespread myth?

Michael Fritsch & Muhamed Kudic

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Abstract

The emergence and solidification of network patterns is typically explained by the preferential attachment rule. The underlying logic is that a small number of actors which are characterized by an above average degree attract links at a higher rate than others. We raise the question as to what extent the wide spread preferential attachment explanation holds true in the context of inventor networks. To shed some light on this issue we investigate co-patenting relationships among inventors in the field of laser technology in West Germany from 1961 to 2005. From a system perspective, the development of the inventor networks is in line with the pattern that is implied by the preferential attachment logic. However, we find high levels of fluidity of micro-level relationships that put the typical transaction cost and trust-based explanation of tie formation processes into question.

Key words: Preferential attachment, inventor networks, system stability, micro-level instability, laser industry

JEL codes: O3, R1, L6, D2, D8

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1. Why do network topologies matter and how do they emerge?

Innovation processes are characterized by a pronounced division of labor between actors (Wuchty et al. 2007) that manifests in networks of relationship. Many empirical studies clearly show that the structure of such networks can have a significant effect on the performance of single actors in a network as well as on the performance of a network as a whole (Kudic 2015). Understanding how and why certain network structures emerge over time is of vital importance for the strategic positioning and related performance outcomes of the actors involved as well as for policy that aims at influencing such processes.

Probably the most widespread explanation for micro-level attachment processes in networks is the preferential attachment rule originally proposed by Barabasi and Albert (1999). Their simple but powerful model is based on two basic ingredients: network growth and preferential attachment (Albert and Barabasi 2002). A key assumption of the model is that actors who were once part of the network remain in the network in subsequent periods. Moreover, it is assumed that the links between actors, once established, are stable over time. This is in line with economic reasoning in cooperation and network research that cooperation requires trust and transaction costs that will be sunk if a relationship were to be abandoned. The underlying logic of the model is based on the notion that a small share of actors—those who are characterized by an above average number of network links—attracts new links at a higher rate than those actors that are less well-connected in the network. For the first time it allowed for an explanation of the emergence of scaling and power-law degree distributions in real-world networks.

Today, the preferential attachment logic, according to Barabasi and Albert (2002), is the prevailing explanation when it comes to linking micro-level processes to the emergence of real-world patterns at higher levels of aggregation. Recent studies (Powell et al. 2005, Garas et al. 2014) cast, however, serious doubt on whether the commonly applied Barabasi-Albert model provides an appropriate explanation for pattern formation in R&D

networks. For instance, Powell et al. (2005) showed that the preferential attachment logic has its limitations. They found that actors in US Biotech connect to one another through in a variety of independent ways. Similarly, Garas et al. (2014) analyzed alliance formation behavior and found that many firms alter their partner selection strategies over time. Particularly, many newcomers tend to first connect with actors that have a high degree of centrality in the network and, after some time, prefer links to less central nodes.

This paper applies co-patenting data at the inventor level to analyze to what extent preferential attachment matters for the emergence of large-scale patterns in R&D networks. The employed dataset is unique in the sense that it covers the patenting activities of all inventors in West German research on laser technology over a relatively long period of time (from the inception of the technology in the year 1961 until 2005). Our study contributes to the current debate on the role of preferential attachment mechanisms in, not only innovation economics, but also in related fields of network research. Our findings have far ranging implications for theoretical reasoning with regard to research cooperation and network evolution.

An in-depth analysis of attachment logics and emerging network topologies is vital for at least two reasons. First, it can help to understand the structural particularities of real-world innovation networks that enable knowledge diffusion and innovation. Second, and even more important in this context, it allows for the identification of structurally resilient areas in the network that shield the network against potential instabilities that may hamper the system’s innovation performance.

The following Section 2 summarizes the main contributions of previous research on pattern formation at the system level and attachment logics at the micro level. We then provide background information on the development of the West German laser industry in the period of analysis and introduce our data (Section 3). Section 4 addresses to what extent how much inventor networks in the German laser industry show typical real-world patterns. Next, we turn our attention to tie formation processes at the micro-level (Section 5). We conclude with a brief discussion of the main findings in the light of the contemporary debate and outline some promising avenues for further research (Section 6).

2. Previous research on pattern formation and attachment mechanisms

2.1 Pattern formation at the overall network level

Research on the emergence of network structures is highly interdisciplinary. Mathematicians (Erdős and Rényi 1959), physicists (Barabasi and Albert 1999; Albert and Barabasi 2002), biologists (Nowak et al. 2010) and sociologists (Milgram 1967; Watts and Strogatz 1998) have significantly enhanced our understanding of pattern formation processes in networks. These and many other studies show that real-world systems that reach from technical systems (e.g. the internet) to socio-economic systems (e.g. innovation networks) are anything but stable and homogeneously structured. Instead, ties are not randomly distributed and one can observe typical pattern formation processes in real-world systems (cf. Albert and Barabási 2002; Newman et al. 2006; Newman 2010). The study of network topologies has also raised considerable attention among economists as well as among scholars in management and organization research.

For instance, Milgram (1967) showed quite early in his famous ‘letter passing’ experiment that people in the US are separated by no more than six steps. The explanation for this highly interesting finding can be based on the structural configuration of the interpersonal network. Ties were not randomly distributed among individuals, and the overall network structure was characterized by short average path-length and high clustering. It took nearly 30 years before scholars were able to quantify the so-called ‘small-world’ phenomenon[1] by applying social network analysis methods (Watts and Strogatz 1998). Several empirical studies have confirmed the co-

[1] Compared to a random model, small-world networks are characterized by significantly shorter average path-lengths and a much higher clustering coefficient (Newman 2010).

existence of short path-lengths and above average clustering coefficients in innovation networks (e.g. Uzzi et al. 2007), as well as, showed that these systemic properties can enhance creativity at the actor's level (Uzzi and Spiro 2005) and may foster firms' ability to create novelty in terms of innovations (Schilling and Phelps 2007).

Similarly, the emergence of core-periphery (CP) structures at the overall network level (Doreian and Woodard 1994) attracted much attention.[2] Some scholars have proposed ways to measure the emergence of core-periphery patterns at the overall network level (Borgatti and Everett 1999). Others have applied these measures in an innovation context and demonstrated that actors who occupy an intermediate position between the core and the periphery in real-world networks outperform others in terms of creative outcomes (Cattani and Ferriani 2008). In an inter-organizational context, it has been argued that the core of sectoral innovation network should contain essential elements of the industry's technological knowledge (Rank et al. 2006).

Last but not least, scaling-properties of networks (cf. Barabasi and Albert 1999; Barabasi and Bonabeau 2003) raised considerable attention. The underlying logic is fairly simple: a small number of actors are rather densely connected while most other actors have only few connections. This, in turn, leads to a systematically skewed degree distribution at higher levels of aggregation.[3] The existence of these patterns has been documented in a broad range of studies. For instance, Powell et al. (2005) analyzed degree distributions of six networks (differentiated by type of partner) over the period 1988 – 1999 in the US life-science industry. The results for all six settings reject the presence of an exponential-decay degree distribution. In other words, degree-plots clearly show power-law slopes indicating that a small number of actors seem to attract a

[2] For a review, see Csermely et al. (2013).

[3] A fat-tailed or scale-free degree distribution of a real-world network can be described as follows: "Unlike the tail of a random bell curve whose distribution thins out exponentially as it decays, a distribution generated by a popularity bias has a "fat" tail for the relatively greater number of nodes that are highly connected. The fat tail contains the hubs of the network with unusually high connectivity." Powell et al. (2005, 1151).

significantly higher number of ties compared to the large majority of other network actors.

To sum things up, by now it is well-recognized that real-world networks tend to exhibit structural properties that differ systematically from random networks. However, we still have a rather rudimentary understanding of the drivers that cause the emergence of real-world network patterns over time. This leads to the question of how far real-world socio-economic systems—innovation networks in particular—differ from randomly generated benchmark networks of comparable size and density. At the same time, it calls for a closer look at the driving forces behind these pattern formation processes.

2.2 Attachment mechanism at the micro level and its economic implications

We are certainly not the first to address attachment mechanism at the micro-level.[4] For instance, Kirman (1993) demonstrated that "herding behavior" can lead to systematic structural biases in economic systems. Davis (1970) and Holland and Leinhardt (1971) have introduced the "triadic closure" mechanism and argued that two unconnected actors (*i*) and (*j*) which are both connected to third actor (*k*) have a higher probability to establish a direct connecting link among one another than establishing a link with another actor (*y*) in the system. Some have argued that similarities between actors ("homophily") increase the probability to connect to one another (McPherson et al. 2001). Other authors have raised exactly the opposite argument by introducing the concept of "heterophily" according to which heterogeneous actors attract one another at a higher rate (Kimura and Hayakawa 2008).

However, by far the most widespread explanation of structuration processes in real-world network networks is the so-called Barabasi-Albert model (cf. Barabasi and Albert 1999; Albert and Barabasi 2002). The

[4] For an interesting compilation of papers and a comprehensive overview, see Newman et al. (2006).

preferential attachment algorithm proposed by Barabasi-Albert is characterized by two features. First, networks are assumed to grow over time. The model starts with a small number of nodes (m_0) and at every time step new nodes (m) connect to existing nodes in the system while it is assumed that the new nodes (m) are different from those nodes already present in the system (Albert and Barabasi 2002, 71). There are no node exits or tie termination processes incorporated in the model. Second, the attachment process is not assumed to be systematically biased. The model is based on the assumption that nodes with a relatively high degree attract new partners at a higher rate than nodes with a lower number of links. Hence, the probability (π) that a new node will be connected to node (i) in the network depends on the degree (ki) of node (i), such that (ibid.)

$$\pi(k_i) = \frac{k_i}{\sum_j k_j},$$

with the denominator being the sum qualifies the sum of links over all nodes.

Numerical simulation shows that after t time steps this procedure results in a network with ($N= t+ m_0$) nodes and m_t edges and the entire system evolves into a scale invariant state (Albert and Barabasi 2002). In other words, the algorithm produces a network structure that is characterized by a fat-tailed degree distribution.[5] One important feature of the model is that a small number of nodes attract—more or less by chance—an above-average number of cooperation ties at the very beginning of the network evolution process. The implemented attachment mechanism ensures that these high-degree nodes continue to attract new partners at a higher rate than the other actors in the system. In other words, once the attachment process has started, a small number of high-degree actors continue to reinforce their highly stable position within the system.

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[5] For an illustration of the network structure generated by the Barabasi-Albert model, see Appendix I. The model generates scaling patterns that are typical for real-world networks (cf. Figure 2a).

The assumptions and predictions of the model are in line with economic reasoning on the role of cooperation in an R&D context. The most evident arguments are certainly related to costs. Repeated cooperation with a well-known partner decreases search costs as well as the effort for establishing a relationship. Similarly, redundant linkages between two partners possess the potential for realizing synergy effects and decreasing cooperation-related costs. Theoretical concept such as the concept of organizational routines, originally proposed by evolutionary economists (Nelson and Winter 1982; Teece et al. 1997), have been applied and adapted to an inter-organizational context to explain superior cooperation (Zollo et al. 2002; Goerzen 2005) and networking capabilities (Hagedoorn 2006) of firms. Once organizations have developed organizational routines from their cooperative relationships, they can save costs by transferring these routines to collaborative relationships with other partners instead of developing new routines more or less from scratch. Hence, one should observe relatively stable relationships in the sense of repeated and redundant cooperation events.

Similarly, it has been claimed that micro-level ties should typically be characterized by a high degree of recurrence of cooperation sequences. There are at least two arguments that support this assumption. First, identifying a suitable cooperation partner and establishing cooperative relationship requires considerable transaction costs that would be sunk if the relationship is abandoned. Hence, actors have a strong incentive to maintain a once established cooperative relationship. Second, since the result of R&D cooperation is ex-ante unknown and, therefore, cannot be completely specified in a contract, such a relationship requires mutual trust of the cooperation partners. Trust is also needed for the exchange of confidential information that may be necessary in such a cooperative relationship (Doz 1996; Das and Teng 2002). In a nutshell, cooperation with well-known partners decreases the risk of unexpected opportunistic behavior and increases the success prospects of joint R&D endeavors.

The implications derived from the Barabasi-Albert model and the theoretical arguments raised above are straightforward. Firstly, the number of actors in a network should grow over time. Second, since the Barabasi-Albert model generates networks with short average path-lengths and high clustering, we expect to find the emergence of typical real-world network patterns such as core-periphery structures, small-world patterns and scaling properties at the overall network level. Third, there should be some central actors with relatively many links that remain in a central position over time. Similarly, the ties structure should show rather stable patterns at the micro level. Both, transaction cost and trust-based explanations of tie formation processes support this line of argument.

3. Industry and data

To shed some light on the micro-level attachment mechanisms in R&D networks we investigate co-patenting relationships among inventors in the field of laser technology in West Germany from 1961 to 2005. The German laser technology provides a well-suited empirical example for analyzing the structural stability of R&D networks because developments in this field require a pronounced division of labor between different actors and institutions. One reason for this special need of cooperation is the science-driven character of laser technology (Bertolotti 2005; Bromberg 1991; Grupp 2000) that requires knowledge transfer between public research and private sector firms. A second reason is that development of laser technology requires expertise from various scientific disciplines such as optics, electronic engineering and physics (Fritsch and Medrano 2015). We draw upon patent data to track the R&D cooperation activities in this technological field.

3.1 The development of laser technology research

The acronym laser was originally coined by Gould R. Gordon (1959) and stands for “Light Amplification by Stimulated Emission of Radiation“. It describes a wide range of devices for the amplification of coherent light by stimulated photon emission generated by pumping energy into an adequate medium. A laser device emits a coherent light beam, both in a spatial and a temporal sense, that can be generated based on different gain media such as solid crystals and semiconductors. The coherent light beam can be modulated and amplified. Laser is a general purpose technology that has a wide range of applications and can be regarded as one of the most important scientific discoveries of the 20th century.

The theoretical foundations of laser technology date back to the year 1917 when Albert Einstein rearranged Max Planck's quantum theory into a light quantum theory postulating the possibility of stimulated light emission (Bertolotti 2005). In 1928, Rudolf Ladenburg and Hans Kopfermann provided the first experimental evidence for stimulated emission, and in the early 1950s, experimental evidence led to speculations about the possibility of generating microwave amplification by stimulated emission.

In 1960, a research group led by Theodore H. Maiman at the Laboratories of the Hughes Aircraft Company in Malibu (California, USA) was the first to succeed in realizing a laser effect, a breakthrough duplicated later that same year by a research group led by Arthur L. Schawlow at the Bell Telephone Laboratories (Bertolotti 2005; Bromberg 1991). News of this success spread quickly around the world creating a buzz in the academic community, a flurry of press releases, presentations at conferences, and academic publications (Maiman 1960a, 1960b; Collins et al. 1960) that became available around the end of that same year generating a general sense of euphoria among scientists.

3.2 Laser technology research in Germany

The first realization of a laser in Germany occurred in the Munich laboratories of the Siemens Company which was the largest private-sector research facility in West Germany at the time (for details see Fritsch and Medrano 2015). Until 1970, Siemens was the dominating firm in laser research in Germany. Starting in the mid-1960s, an entire industry emerged that was characterized by a high number of newly founded small firms (Buenstorf 2007).

According to Grupp (2000), the laser industry experienced a long initial experimentation phase of more than 20 years that has been characterized as a “solution in search of a problem” (Bromberg 1991). It was only around 1982 that the market for commercial laser products took off, and the expansion phase of this technology began (Grupp 2000). When the industry took off, the technology quickly diversified and began to be integrated into diverse types of commercial applications (Buenstorf et al. 2012).

3.3 Data sources

Our empirical study is based on patent application data. It is commonly agreed that a patent application indicates an innovation effort. Similarly, co-patenting activities are frequently used as an indication of collective innovation processes jointly conducted by two or more actors. From the patent data we obtained information on the applicant organizations and all of the inventors that have made significant contributions to the invention that allow us to identify links between these actors.

We have gathered patent application data for the entire population of inventors in the broader field of laser technology in Germany over a period of 45 years from the inception of the technology in the year 1961 until 2005. These data were obtained from the database DEPATISnet (www.depatisnet.de), which is maintained by the German Patent and Trade Mark Office, and from the DOCDB database of the European Patent Office (www.epo.org), which has worldwide coverage. From these sources we selected all patent applications with priority in West Germany that were assigned to the technological field “devices using stimulated emission” (IPC H01S) as either the main or secondary class. Research in this IPC class is related to laser beam sources that constitutes the basis for all kinds of applications. We also account for important applications of laser technology by including those patent applications in the fields of material processing (IPC B23K), medical technology (IPC A61 without IPC A61K) and spectroscopy (IPC G01N) that mention the term “laser” in the document.

3.4 Methodological consideration on the use of co-patenting data for network analyses

The construction of inventor networks based on co-patents requires some additional assumptions. Generally, we regard two particular inventors as being linked if they are both named on the same patent application. For the purpose of this study, we stick to the assumption that each inventor of a co-patent with more than two inventors has a relationship to all other inventors named on the patent so that the internal structure is best represented by a fully connected undirected graph. This implies that information between two actors can be exchanged in both directions.

Dividing the observation period into sub-periods implies that the duration of a cooperative tie is limited to that period if the respective inventors are not mentioned together on another patent in the subsequent period. This assumption is necessary since patent data provides no direct indication of tie-duration or tie-termination dates.

3.5 Basic descriptives on co-patenting activities and team size

Innovation processes are increasingly characterized by a division of labor between different actors and institutions. This trend towards more R&D cooperation is well reflected in our data. We split the observation period into nine sub-periods each covering a five-year interval. The priority filing date of the underlying application is used to assign the co-patenting relationships to the respective sub-period. In total, we are able to identify 4,381 laser-related patent applications with German inventors.

Table 1 depicts some descriptive statistics for the patent data gathered for the period between 1960 and 2005. In the first observation period (1961-65) we found only 53 co-patents which amount to 31 percent of all patents in this period. Looking at the second sub-period (1966-70) reveals a remarkable increase in both single and co-patenting activities. In the mid-70s the number of co-patents exceeds that of single patents for the first time. The subsequent periods are characterized by a strong increase in co-patenting activities, whereas the number of single patents rises only at a modest pace. In the last time interval (2001-2005) more than 71 percent of all patent applications have two or more inventors.

Table 1: Descriptive statistics – number of single patents and co-patents over time

	1961-1965	1966-1970	1971-1975	1976-1980	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	Sum
Single patents	117	178	142	130	140	242	243	268	251	1.711
2 inventors	41	75	68	73	112	177	194	226	196	1.162
3 inventors	9	29	28	40	66	121	122	177	208	800
4 inventors	3	3	11	16	21	46	76	112	117	405
5 inventors	0	1	6	2	7	15	40	41	53	165
6 and more inventors	0	1	0	5	7	10	26	36	53	138
Co-patents (all)	53	109	113	136	213	369	458	592	627	2.670
Patents (all)	170	287	255	266	353	611	701	860	878	4.381
Average team size	2.28	2.39	2.60	2.75	2.76	2.82	3.12	3.18	3.37	-

Over the entire observation period the number of single-inventor patents has doubled, while the number of co-patents increased by a factor of about 12. Not only the total number and share of co-patents but also the number of inventors per team has increased from 2.28 in the 1961-65 period to 3.37 in the period 2001-2005. In all observation windows smaller teams of two, three or four co-inventors account for the majority of the co-patents. The last category includes all patent applications where the number of co-inventors ranges between six and twelve.

4. Network properties at the overall network level

We begin our investigation of the German laser industry inventor network with a brief look at the topology and some basic properties of the networks. Figure 1 provides an overview of the development of basic network properties over the nine sub-periods. Both, the number of nodes as well as the number of ties, have considerably increased over time.

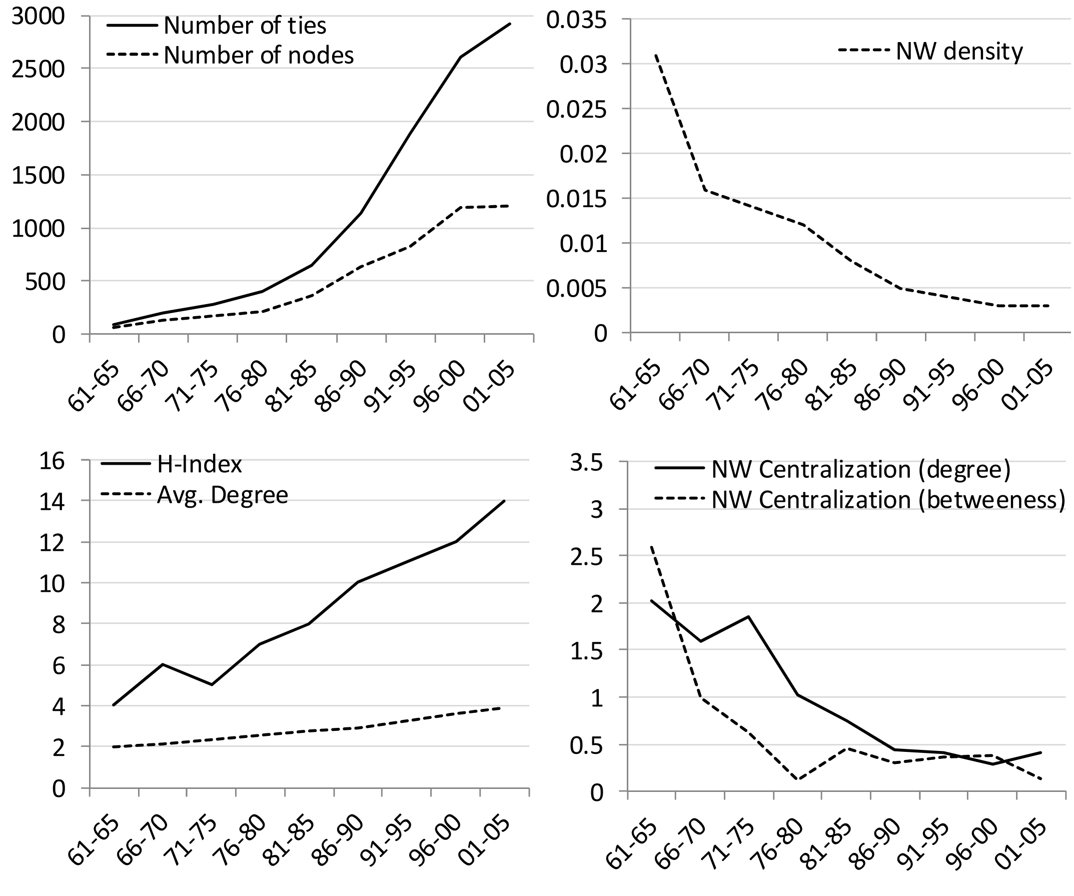

Figure 1: Basic properties of the German laser industry inventor network

The disproportional increase of ties is reflected in the upwards sloping H-Index[6] and average network degree trend-lines. Such a pattern is frequently interpreted as a first indication that a small number of exposed actors attract ties at a higher rate as compared to the majority of

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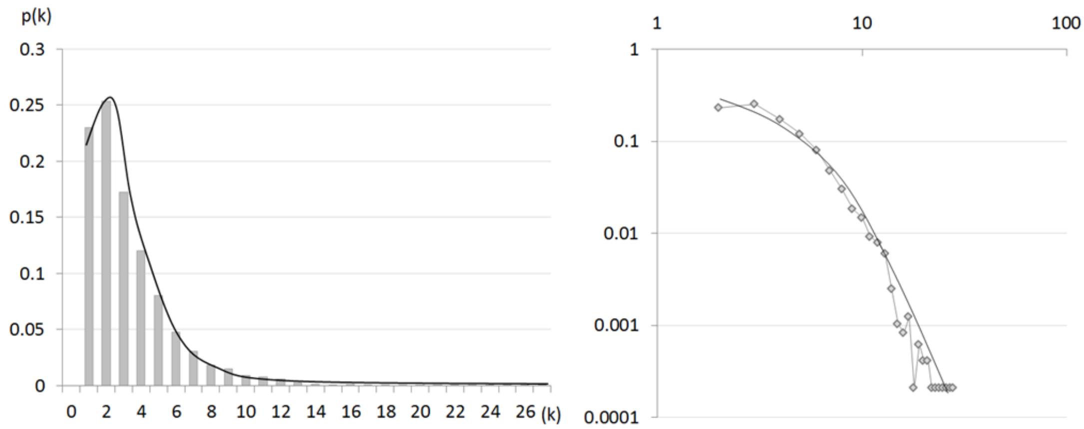
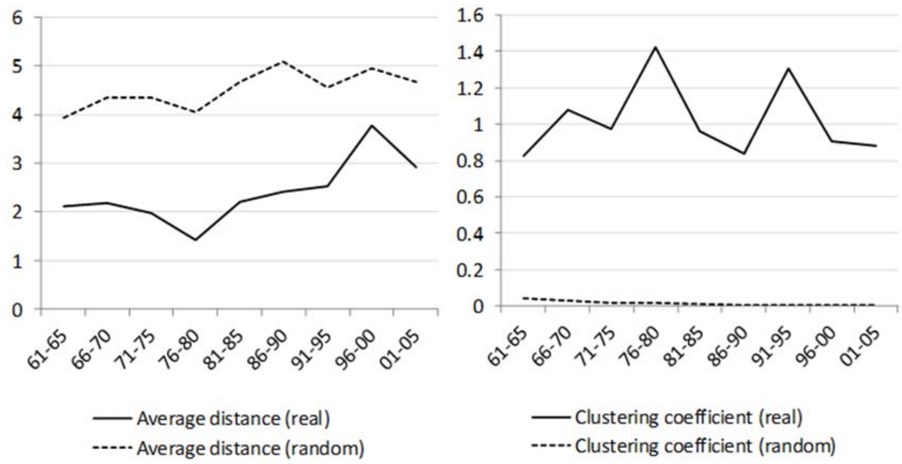
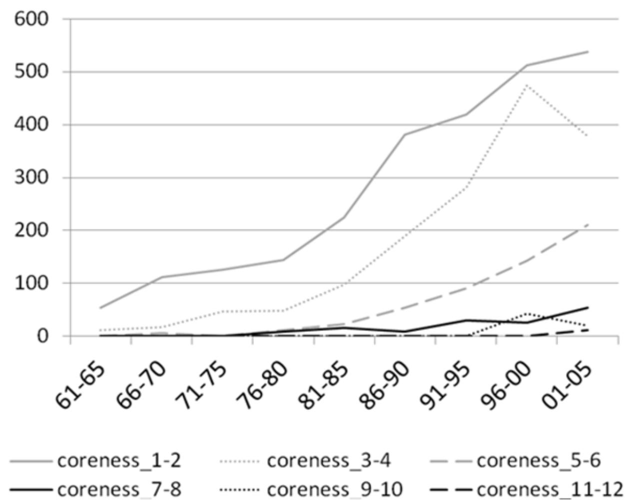
[6] According to Campitelli et al. (2010) the H-index of a node can be defined as the largest integer h such that the node has at least h direct neighbors which have a degree of at least h. The plot shows an aggregated H-index for the German laser industry inventor network.



2a Degree distribution and “scaling patterns”



2b Average path-length, clustering and “small world” characteristics



2c k-core strata and “core-periphery” properties

Figure 2: Structural properties of the German laser industry innovation network

inventors in the network. We find a quite low and decreasing network density at the overall network level. The degree-based and the betweenness-based indices for network centralization are also declining. In a next step we compare the German laser industry inventor network with a random network with regard to three characteristics: (i) overall degree distribution, (ii) small world properties, and (iii) core-periphery properties (Figure 2).

For exploration of the overall degree distribution we calculated the individual degree for each inventor in each of the nine sub-periods. Figure 2a shows the degree distribution for the entire observation period. The abscissa of the histogram on the left represents the degree (k), while the ordinate measures the fraction of nodes in the network p(k) for each degree value. The most frequently observed degree value amounts to 2, while the highest observed degree value is 27. The graph on the right hand side of Figure 2a shows the log-log scatter plots of the degree distributions. According to Newman (2010, 249), an ideal-typical scale-free degree distribution should be monotonously decreasing over the entire range of observations and should result in a negatively sloped straight line in a log-log plot. The curve in the log-log plot of Figure 2a comes quite close to the theoretically optimal form indicating a scale-free structure.[7] In contrast, a random degree distribution would be reflected by a bended curve progression towards the upper right in the log-log plot. In other words, the overall degree distribution of the German laser industry innovation network systematically differs from a pure random network.

In order to check for small-world properties of the laser networks we employ the method proposed by Watts and Strogatz (1998). We begin with repeatedly generating Erdös-Renyi random graph networks[8] which are comparable to the real-world network graphs in terms of size and density. In a subsequent step, we calculated clustering coefficients and average path-lengths for the German laser industry innovation network and its random counterparts. Finally, we repeated this procedure for each

7 Note that the Barabasi-Albert model reproduces these structural characteristics at the system level quite well (cf. Appendix I).

8 In its most basic sense a random network is defined as a system consisting of a well-defined number of nodes. The attachment logic is quite simple. Nodes attract ties with the same probability and there is no systematic bias.

of the networks in the nine sub-periods; the results are reported in Figure 2b. The graph on the left hand side reports the average path-length, while the illustration on the right gives the clustering coefficient for both the real world network and the random benchmark over time. As expected, the average path-lengths of the real-world network are much lower compared to the random benchmark. The clustering coefficients of the real-world networks are highly volatile oscillating around the value of about 1.0 with no clear time-trend. In contrast, the clustering coefficients of the random network range at a much lower level with a tendency to decrease over the observation period.

Last but not least, we address the question as to what extent the German laser inventor networks shows core-periphery properties. The core-periphery concept is based on the notion of "[...] a dense, cohesive core and a sparse, unconnected periphery" (Borgatti and Everett 1999, 375). Technically speaking, the specification of a network core is nothing else but the specification of a cohesive subgraph by using concepts such as n-cliques, k-plexes, k-cores and related concepts (Doreian and Woodard 1994, 269). There is, however, still no consensus in the literature on how to identify core-periphery patterns (cf. Kudic et al. 2015).

We employ the k-core concept and analyze how the k-cores distribution over all inventors in the network changes over time. A k-core is defined as "a subgraph in which each node is adjacent to at least a minimum number, k, of the other nodes in the subgraph" (Wasserman and Faust 1994, 266). Figure 4c provides the results. We find a highly unequal distribution of coreness values over time. The high and increasing dispersion between low level coreness values (i.e. coreness_1-2 and corness_3-4) and high level coreness values (i.e. coreness_9-10 and corness_11-12) indicates the presence and solidification of a core-periphery structure over time.

To sum up, the results of these basis explorations at the overall network level are in-line with what can be expected based on the theoretical considerations outlined above (Section 2). However, results of most recent studies (Garas et al. 2014) cast some serious doubt on the assumption of micro-level stability. This raises the question if these typically emerging overall network patterns are accompanied by stable structures at the level of individual actors and cooperation ties? In how far does this assumption of micro-stability hold?

5. Taking a closer look at the micro-level

In this section we focus on the micro level relationships. We start with analysis at the node level and explore the reoccurrence of actors over time by comparing the number of identical nodes for each sub-period with the all subsequent observation windows.

Table 2: Node re-occurrence for the full population of inventors

	1961-1965	1966-1970	1971-1975	1976-1980	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005
1961-1965	--	8.54	3.80	0.72	0.94	0.00	0.11	0.08	0.16
1966-1970	199	--	10.13	5.49	3.25	1.04	0.84	0.38	0.15
1971-1975	237	306	--	13.02	6.78	2.49	1.41	0.88	0.14
1976-1980	277	346	384	--	11.03	4.50	2.71	1.14	0.56
1981-1985	424	493	531	571	--	9.28	4.50	2.96	1.59
1986-1990	697	766	804	844	991	--	10.95	5.58	3.69
1991-1995	885	954	992	1032	1179	1452	--	10.71	6.00
1996-2000	1261	1330	1368	1408	1555	1828	2016	--	12.54
2001-2005	1277	1346	1384	1424	1571	1844	2032	2408	--

Table 2 reports the number of identical nodes (inventors) across the different sub-periods for the entire network. The values in the lower part below the diagonal report the number of inventors for two compared time periods. The values above the diagonal line are the shares of identical actors (in percentage terms) for two compared time periods. Surprisingly, we find a very low level of structural stability at the node level.

All in all, the results are quite remarkable. The maximum share of identical actors in two subsequent time periods is only 13.02 percent. This share strongly converges towards zero with the time distance between the sub-periods periods. This rather high fluctuation of network nodes (inventors) over time indicate a low structural stability at the node level.

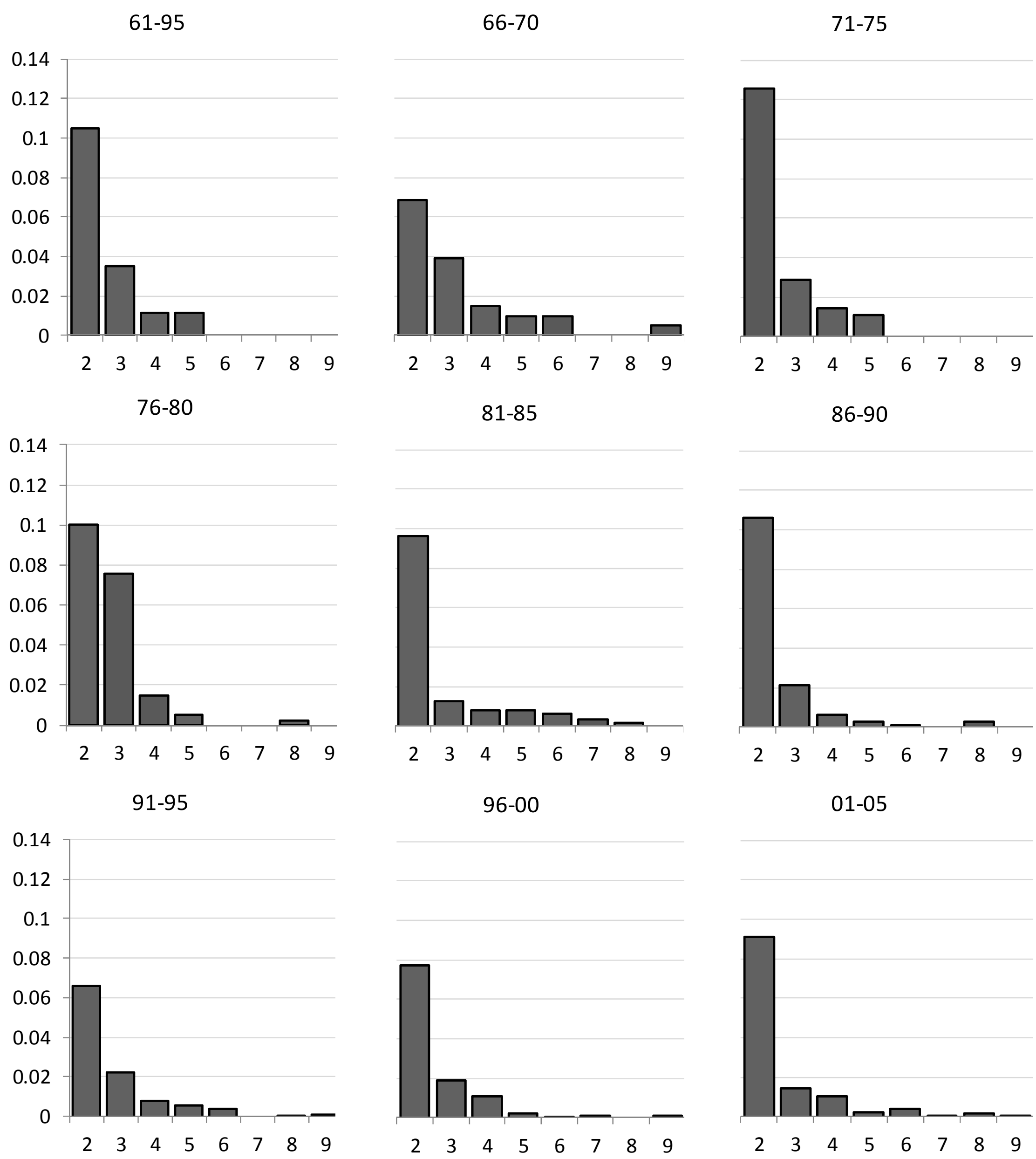


Figure 3: Degree of cooperation redundancy, 1961 – 2005

The analysis of node reoccurrences does, however, reflect only a part of the story. A second important issue is the stability of ties among the actors. Figure 3 provides a differentiated picture of the degree of redundant linkages over the entire observation period.

The histograms illustrate the degree of redundancy for each of the nine periods (figures are reported in the table below). A degree of redundancy of 4 means that there are four ties between a pair of network nodes. Not surprisingly, double bonds (degree of redundancy = 2) appear most frequently, while pairs of nodes that are connected by 9 or more redundant ties occur only very rarely (cf. periods: 66-70; 91-95; 96-00; 01-05). In other words, redundant cooperation structures are rather rare; they can be typically identified at the dyadic level.

Let us now briefly recapitulate the results from the overall network redundancy analysis in Section 4 (cf. Figure 2c). We found—with some minor exceptions—a high level of efficiency indicating that the degree of redundant connections is remarkably low, but we had no explanation for the peak in terms of network redundancy in the sub-period 1976-80. Our tie redundancy analysis at the micro level may provide some reasons why the German laser industry innovation network shows this structural pattern. Table 3 reports for each degree of redundancy in terms of percentages. The maximum percentage terms (for each degree of redundancy class) are highlighted in italics. The average percentage values over the entire observation period are reported in the right column.

What stands out in the period 1976-1980 is the fact that dyadic linkages do not play a dominant role in maintaining structural stability in terms of redundancy. Instead, constellations of actors consisting of three redundant ties (7.58%) and constellations of actors with four redundant ties (1.47%) seem to be the sources of structural stability in the sub-period 1976-80. Not only the period 1976-80, but also the preceding period (1971-75), as well as the succeeding period (1981-85) are characterized by an above average degree of redundancy at the overall network level (Figure 2c). Our micro-level exploration shows that the drivers behind these patterns are very different. In the period 1971-75 the above average level of overall network redundancy is driven by a high number of double bonds. In the second case, the 1981-85 period, the above average level of overall network redundancy is driven by a comparatively small number of highly redundant interconnected pairs of inventors.

Table 3: Degree of redundancy in percentage terms, 1961 – 2005

		61-95	66-70	71-75	76-80	81-85	86-90	91-95	96-00	01-05	
Total number of ties:		86	205	278	409	643	1135	1888	2615	2922	
Number of unique pairs:		64	140	203	273	491	908	1332	2166	2360	
											Average
Degree of redundancy (%)	2	10.47	6.83	*12.59*	10.02	9.64	10.57	6.57	7.72	9.10	9.28
	3	3.49	3.90	2.88	*7.58*	1.24	2.11	2.22	1.91	1.44	2.98
	4	1.16	1.46	1.44	*1.47*	0.78	0.62	0.79	1.07	0.99	1.09
	5	*1.16*	0.98	1.08	0.49	0.78	0.26	0.53	0.23	0.24	0.64
	6	0.00	*0.98*	0.00	0.00	0.62	0.09	0.37	0.04	0.38	0.27
	7	0.00	0.00	0.00	0.00	*0.31*	0.00	0.00	0.11	0.03	0.05
	8	0.00	0.00	0.00	0.24	0.16	*0.26*	0.05	0.00	0.14	0.09
	9	0.00	*0.49*	0.00	0.00	0.00	0.00	0.11	0.08	0.03	0.08
Overall degree of redundancy:		16.28	14.63	17.99	19.80	13.53	13.92	10.65	11.17	12.35	
Standard.deviation		3.61	2.37	4.30	3.99	3.24	3.64	2.24	2.64	3.10	

Last but not least, we investigate how frequently connections between pairs of actors are stable over time (Figure 4). Thus, for a moving reference period (from 1966-70 until 2001-05) we explored as to what extent linkage between inventors have already existed in previous observation periods (Figure 4). The cooperation patterns shown by Figure 4 can be interpreted as the total cooperation duration between pairs of actors. The exploration nicely shows that the inter-temporal connectivity of the German laser industry innovation network is comparably high in the directly preceding period (cf. reference year: 1981-85) but much lower in earlier periods. The existence of repeated ties reaches back for a maximum of only three prior periods (cf. reference years: 1991-95; 1996-00; 2001-05). Very rarely do we see a repeated linkage earlier than that (cf. reference year: 1986-90).

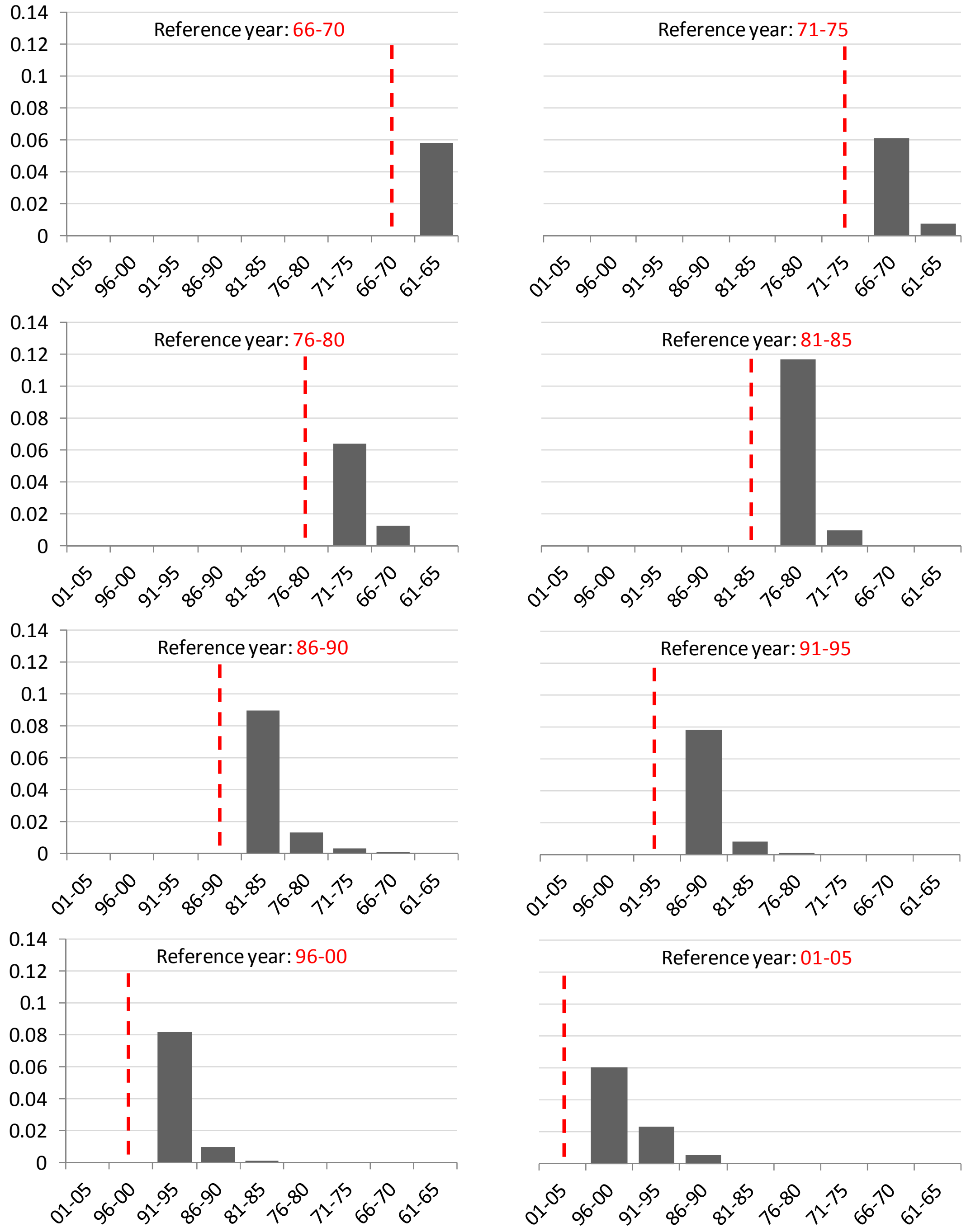


Figure 4: Repeated ties (cooperation sequences), 1961 – 2005

6. Discussion and conclusions

At the very heart of this paper we addressed the question as to what extent the widespread preferential attachment assumption provides an appropriate explanation for the emergence of typical pattern formation in R&D networks. The answer to this question is as simple as it is surprising: preferential attachment plays no significant role at the micro level. Instead, we observe an extremely high level of fluctuations both at the node level and at the tie level. This insight is based on longitudinal explorations of structural inventor network characteristics based on patent application data in German Laser research. Our data covers a period of forty-five years starting with the inception of this research field in 1961 until 2005.

Our analyses at the overall network level reveal some interesting insights. We found that the propensity for co-inventorship, as well as the average size of inventor teams, did considerably increase over time. The development of basic network properties (Figure 1) indicates a high level of structural stability. The inventor network of German laser research exhibits a fat-tailed degree distribution, shows a core-periphery structure, and has typical small-world properties. At least at first glance these results indicate a high level of structural stability at higher aggregation levels. In particular, these patterns are perfectly in line with the preferential attachment logic and economic reasoning on transaction-costs and trust building processes through repeated and redundant cooperation activities among same actors. However, zooming into the micro-level provides a completely contradictory picture. Our explorations at the micro-level show a very low degree of node reoccurrence over time. The same holds true for the tie dimension. We found an extremely low level of redundant and repeated cooperation activities.

All in all, our analyses show that the links between inventors in networks, based on patents, are characterized by a high level of instability at the micro-level. Obviously such networks are highly volatile and transient so that the resulting network graphs and parameters have to be regarded as snapshots of a highly dynamic process. The picture of a high level of structural stability that is found at the overall network level is deceptive as it conceals high levels of intertemporal fluctuations of both nodes and ties under the surface of the system.

What certainly can be learned from this exercise is that the well-known preferential attachment mechanism—frequently applied to explain pattern formation in real-world networks—plays no significant role in the inventor network of the German laser industry. Our findings are in line with Garas et al. (2014, 4) who found that “[…] even if new nodes have the preference (and the incentive) to create links with central nodes, in reality they end up linked with other new nodes (i.e. nodes with similar centrality) or with the less central existing ones.” Obviously, not the preferential attachment rule but other rationales and mechanisms at the micro-level seem to fuel the typical pattern formation processes in the patenting networks of German laser research. Our result is also consistent with the findings of Powell et al. (2005) who argued that exploration-based cooperation strategies of actors seem to generate a much more robust explanation for network evolution processes than exploitation based strategies such as a multiconnectivity attachment mechanism.

Currently, not much is known about more realistic attachment rules at the micro-level of R&D networks (the most notable exception is Powell et al. 2005). Despite of the huge interest in network evolution processes we are still at the very beginning of understanding how micro-level processes affect the structuration and dynamics of complex systems. Based on the current state of knowledge we also can only speculate in how far a high level of network fluidity has to be judged as positive or negative for the generation and diffusion of knowledge. On the one hand, high flexibility in the formation of inventor teams may indicate an effective allocation of talent and a fast diffusion of knowledge. On the other hand, weak ties between inventors may not involve much trust and can have their limits with regard to the quality of the knowledge exchange.

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Appendix I

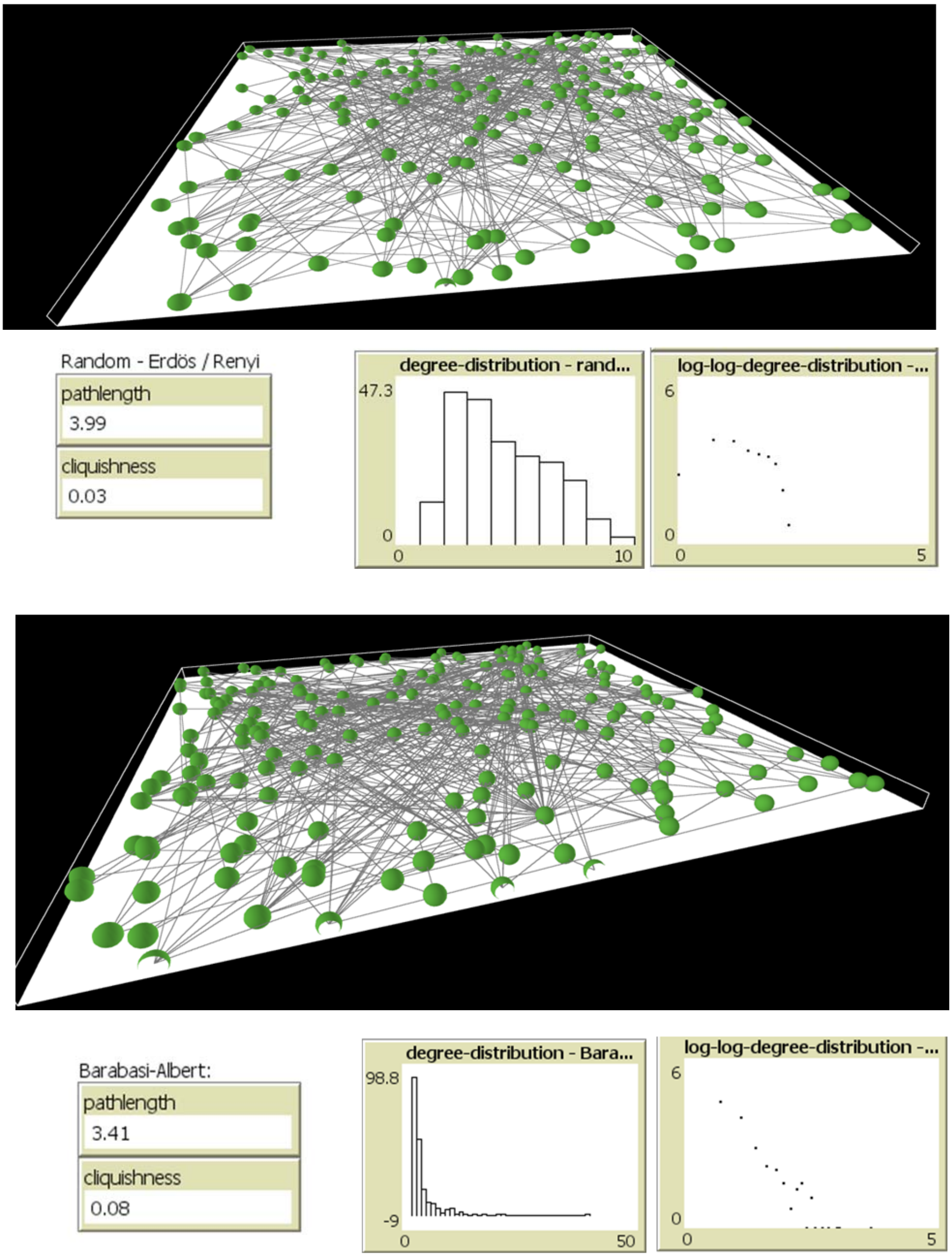

Figure A1: Artificial network – „Erdös-Renyi“ vs. „Barabasi-Albert“ model
Source: Simulation model applied in: Müller et al. (2015)