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A TAXONOMY OF INNOVATION NETWORKS

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ABSTRACT

In this discussion paper we develop a theory-based typology of innovation networks with a special focus on public-private collaboration. This taxonomy is theoretically based on the concept of life cycles which is transferred to the context of innovation networks as well as on the mode of network formation which can occur either spontaneous or planned. The taxonomy distinguishes six different types of networks and incorporates two plausible alternative developments that eventually lead to a similar network structure of the two types of networks. From this, important conclusions and recommendations for network actors and policy makers are drawn.

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Introduction

The investigation of innovation networks in different settings as well as the assessment of their performance as a result of their respective characteristics requires the employment of a suitable taxonomy. However, developing such a taxonomy is not an easy task. Innovation networks are not static but permanently evolving in their most characteristic features such as their composition and structure and sometimes even with regards to their research directions and goals. Additionally, these processes are highly interrelated and co-evolutionary and, thus, hard to be distinguished and analyzed individually. These changes are mostly small and incremental and endogenous to the network. They are taking place permanently but not continuously during the network evolution. This complicates the identification, distinction and comparison of innovation networks since the observed differences might simply be due to different stages in the life-cycle of the respective innovation networks. Thus, any useful typology of innovation networks has to take into account these co-evolving dynamics.

A theoretically and empirically well-founded concept that incorporates these dynamic aspects and at the same time allows for a clear cut distinction of the different stages is the life cycle concept. The life cycle concept was successfully applied and tested in the context of manufacturing industries and their underlying products and technologies (Abernathy and Utterback, 1978; Jovanovic, 1994; Klepper, 1996; 1997). The basic idea of the concept is to divide the evolution of industries into sequential and distinguishable stages. Such stages also shape the evolution of innovation networks, which makes the concept of life cycles a valuable tool in investigating the evolution of innovation networks.

While the life cycle concept enables us to distinguish innovation networks along their development path, we also need a characteristic feature to explain the observable differences between innovation networks that are at the same stage of their life cycle. This is done by introducing the mode of network formation as the second dimension to our taxonomy. Here, empirical evidence suggests that there are basically two modes in which a social network is formed – it either emerges spontaneously or is created in a planned manner. Since the mode of network formation has an enduring impact on the fundamental network characteristics and their evolution the incorporation of this dimension allows us to distinguish and compare therein distinct networks even when they are at the same stage of their respective life cycle.

Finally, the observable differences between the diferent types of innovation networks have to be identified quantitatively in order to make them empirically comparable. Since innovation networks are composed of actors and the relations and interactions between them, the social dimension is of uttermost importance in this context. Thus, we need a methodology that allows us to incorporate the social aspects of interaction and cooperation as well as the peculiarities of the respective network composition and structure. A methodology that incorporates all these features is the Social Network Analysis (SNA). Combining the concepts of life cycles and modes of network formation and applying methods and indicators from social network analysis to identify and distinguish different network types will provide us with a comprehensive typology of innovation networks that meets the requirements of investigating public private innovation networks in services.

The Life Cyle Concept in the Context of Innovation Networks

The discovery of the industry life cycle (ILC) has been one of the most important developments in industrial dynamics of the last thirty years. Many sectors have been found to follow a similar development path, going through the same series of stages which can be described as a life cycle (Abernathy and Utterback, 1978; Jovanovic, 1994; Klepper, 1996; 1997). Given that an ILC is followed by many but not by all the sectors, a very important question arises concerning the determinants of and the conditions under which an ILC can be observed. The literature has provided a number of answers to this question. In the following we review the literature on the nature and dynamics of the ILC before transferring it into the context of innovation networks.

The concept of ILCs has had a number of precursors. Relevant examples of these concepts are dominant designs (Abernathy, Utterback, 1975), technological regimes (Nelson, Winter, 1977), technological paradigms (Dosi, 1982), technological guideposts (Sahal, 1985) and the concept of the product life cycle (Vernon, 1966, Gort and Klepper, 1982). As it turns out all the sectors for which a life cycle was observed are implicitly defined by products and production technologies. However, it was not until the 1990s that the term 'industry life cycle' was regularly used. The scholars who contributed to the study of ILCs did not simply change the term but considerably improved our understanding of the underlying dynamics.

The ILC is usually characterized by the existence of seven regularities or principles of evolution (see Klepper 1996 and Saviotti et al. (2007):

- Entry is dominant in the early phases of the life cycle while exits progressively dominate in the course of the cycle
- First movers generally have a leadership position which guarantees their long-term viability and, thus, firm size increases in the course of the cycle
- Market shares are highly volatile in the beginning but tend to stabilize over time
- Production increases in the initial stages and declines in the final stages
- Product innovation tends to be replaced by process innovation
- Product variety disappears over time and a dominant design emerges
- A massive process of exit (shakeout) occurs in the later stages of the life cycle

These characteristics lead to the well known sequence of stages in life cycle concepts. While there is some variance in the number of distinct stages in the different life cycle concepts there are four broader stages that are generally distinguished: The initial stage (also fragmentation or emergence), the growth stage, the maturity stage (also shake-out), and finally the decline stage. This leads to the ILC development path as illustrated in figure 1.

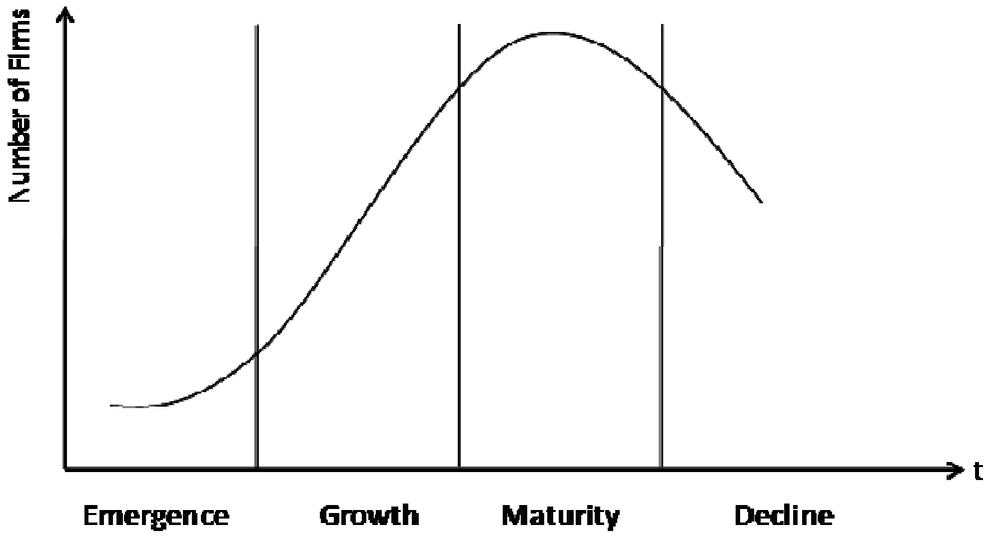

Abbildung 1: The four general stages of the life cycle concept.

In the remaining of this section we apply the ILC concept to the evolution of public private innovation networks. This proceeding is based on the assumption that networks, just as industries and technologies, undergo several distinguishable phases which are shaped by processes similar to those of industries.

In the ILC concept the initial **emergence stage** is characterized by the entrance of the first entrepreneurial firm(s) setting up a business to commercialize their invention (Ayres et al., 2003). By this they actually transform the invention into an innovation. The entrepreneur is quickly followed by some early followers (imitators) seeking a head start to realize early mover advantages. The number and rate of new entrants at this stage is still quite low. Also, the firms in the industry are still rather small as is the output produced by each of them. Since the underlying technology is in its infancy it has not yet created a large demand. Furthermore, the associated knowledge base can be expected to be geographically and institutionally specific (Van Beuzekom, 2001; Van Reenen, 2002). In biotechnology, for example, experts were located in a handful of US and UK universities (Orsenigo, 1989). For the internet it was a few US universities, the US military (ARPANET), and CERN (European Organisation for Nuclear Research). These examples also illustrate that public support and financing can be essential for the development of the basic technology at this early stage of the life cycle (McMillan et al., 2000). Government policies in this proto-industry stage are likely to be local in a geographical and structural sense. They may take the form of piecemeal, local regional funding projects and/or academic research grants (Caracostas and Muldur, 2001). Such flexible public support might be appropriate at this stage of the life cycle, given the high degree of risk associated with highly specialized embryonic technologies, the high number of technology failures that occur, and the fact that the relevant technological knowledge is not yet widely diffused (Coombs and Metcalfe, 2002; Walsh and Rodorfos, 2002).

Transferring this stage of the ILC to innovation networks we are talking about the process of network formation. Following theoretical reasoning and empirical evidence network formation can either be triggered by an enabling actor or emerge spontaneously in a self-organised manner. We will discuss these formation processes and their implications for the network composition and structure in more detail below.

The consecutive **growth stage** of the ILC is characterized by an increasing number of firm entries. At this stage a new industry emerges. The central activity at this stage is the marketization of the new technology. Competition is continuously intensifying as competitors start to realise business opportunities. The new entrants have a disproportionally large share in (incremental) product innovations, providing them with the incentive to enter the market (Klepper, 1996). The new start-up firms are the major innovators and become key players in the emerging industry (e.g. Saxenian, 1994 for ICT industry in Silicon Valley). With the high entry rate the number of competing versions and technological standards increases. At the same time the firms grow bigger in size and output. However, the firm growths as well as the associated market share are subject to permanent change. No incumbent firm has yet established a dominant position or enforced a technological standard.

Applying these ideas to innovation networks we observe a rapid expansion in the number of members as well as in their diversity. Again, there are different scenarios or mechanisms by which a network can grow. One scenario resembles a snowball-pattern in which new members are recommended by the latest newcomers, who themselves were recommended by earlier network members. Another scenario is the selection and invitation of new members by just one or a few very central actors of the core network. This latter scenario is more likely in networks that were initiated by one or a few enabling actors – such as government agencies or departments. Again, we will discuss these scenarios in more detail below.

The **maturity stage** (shake-out) is characterized by a turning point: The net number of firms declines because the exit rate exceeds the entry rate.[1] Due to the various substitutive products and technologies the competition intensifies. The individual firms have to increase their market share or are forced to exit the market. Thus, we observe a shift in the innovative focus from (incremental) product innovation to (cost-reducing) process innovation which allow for the realisation of economies of scale (Abernathy and Utterback, 1978; Utterback and Suarez, 1993; Utterback, 1994; Klepper 1996 and 1997). This shift to cost-based competition leads to the observed shake-out, which decreases the density of firms in the respective industry. As a result, vertical and horizontal integration lead to increasing market concentration and the variance in market shares and innovativeness decreases favouring larger firms.

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[1] The first increasing and later decreasing number of firms is the most consistent regularity found in ILC literature. Of course, the maximum number of firms as well as the lower value attained in mature phases vary considerably between industries. However, the qualitative pattern is robust. In industrial dynamics different explanations for this shake-out are offered. While Utterback and Suarez (1993) explain it with the emergence of a dominant design, Jovanovich and MacDonald (1994) assume external technological shocks, whereas Klepper (1996) argues that the timing of entry is determining the shake-out.

Despite the broad observability of the shake-out in ILCs some authors argue for a relatively long and stable maturity phase instead of the rather sharp turning point in the number of firms. In other concepts further innovations disrupt the ILC at the maturity stage leading to the start of a new cycle within the same industry (Tushman and Anderson, 1986). The decline stage is postponed for those firms that are able to adopt the new technology. This leads to a development in which the industry growth rate varies around a certain level (see figure 2); however, it might also lead to an overall growth of the entire industry with every innovation increasing the size of the market and the corresponding number of firms (see figure 3).

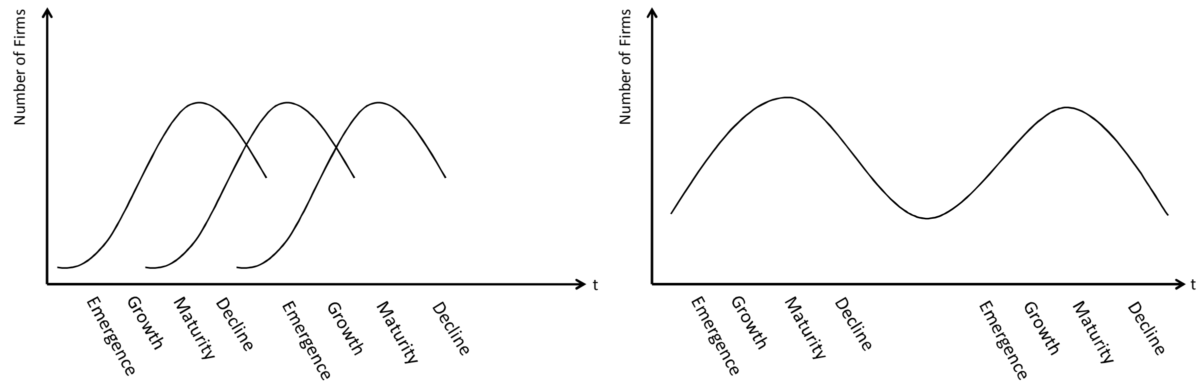

Abbildung 2: Figure 2: Cycle-Recycle based on Tushman and Andeson (1986; 1990). [2]

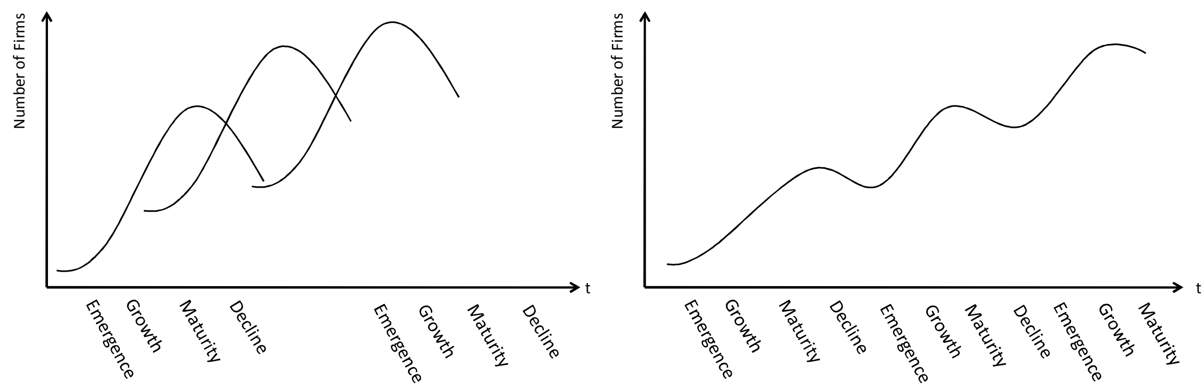

Abbildung 3: Innovative Maturity. [3]

The maturity stage of innovation networks is characterised by intensive interaction and considerable knowledge flows. At this stage learning and knowledge generation reach their peak. As the underlying technology becomes more application-orientation the focus shifts from exploration to exploitation and from radically new solutions to their incremental improvement. This is reflected in the network architectures and structures as well as in the roles played by

[2] See also Cox (1963) and Cunningham (1969).

[3] See Buzzell (1966).

the different actors. The resulting network structures range from a star-network (i.e. there is a central actor that decides, coordinates and controls all interactions within the network) to a completely connected network (i.e. democratic decision-making, self-organisation and self-control). This has obvious consequences for the roles played by the actors in the respective networks (e.g. central actors, peripheral actors, equal actors etc.) as will be discussed in more detail below.

The **decline stage** of the ILC is characterised by what Schumpeter called 'creative destruction'. The mature industry is threatened by new technological developments that substitute its products and services. Because of the decreasing demand (market saturation and a shift towards the new products and services) many companies are forced to leave the industry, occupy a niche or come up with further innovations.

In the context of innovation networks this corresponds with the dissolving of the network because the networks' purpose is accomplished (i.e. the generation, commercialisation and diffusion of innovation). However, for the purpose of this paper the decline stage is not of interest and, thus, will be left aside in the following.

In order to develop a useful taxonomy of innovation networks we have to introduce a second dimension that allows us to explain the differences between networks that are at the same stage of their life cycle. As it turns out, the mode of network formation is crucial in explaining these differences with respect to network characteristics such as structure, composition and the roles played by different actors. Therefore, the next section discusses the determinants of the mode of network formation and its implications for the subsequent network evolution.

The Mode of Network Formation as a Second Dimension of the Network Typology

In this section we introduce the second dimension to our taxonomy of innovation networks: the mode of network formation. This dimension is important because the mode of network formation has major implications for the composition, structure and evolution of networks. In principle, two modes of network formation can be distinguished: A network can either be created in a planned manner by an enabling actor or it can spontaneously emerge (see Powell et al., 1996; Koza and Lewin; 1999; for an overview see Doz et al. 2000).

The following section is largely in line with the study by Doz, Olk, and Ring (2000) who summarize the existing literature and conduct a large scale study to investigate the two types of network formation. Their analysis shows that the actual mode of network formation depends to a large extent on the existence of environmental pressure or opportunities in the form of economical, technological, legal or demographic changes (e.g. increasing global competition, the emergence of new substitutive technologies, environmental pressure, economic liberalization etc.). Addressing such a threat or opportunity often requires some sort of innovation. Thus, there is an incentive for groups of actors to innovate in the same direction. Firms that are active in the same industry, for example, not only share the same environment but also react similarly to changes in their environment. Thus, they develop a common interest when being confronted with such external shocks. In this way, environmental pressure leads to an alignment of interests among the actors of an industry, market or an otherwise defined group of actors. The environmental pressure and shared interest also facilitate the formation of familiarity and trust among potential network partners, which, in turn, moderate opportunistic behaviour and facilitate collaboration (Uzzi, 1997). The more severe the possible consequences of these external changes are the less need there is for an enabling actor to trigger network formation. Thus, in the presence of environmental pressure and the resulting alignment of interests networks may emerge ***spontaneously*** and in a ***self-organised*** manner.

In cases in which the common interest or the necessity to collaborate is hard to see for the individual actors, an enabling actor (syn.: central planner or triggering actor) is needed to initiate network formation. This might be the case when the underlying technology is not well specified, the relevant knowledge is tacit or difficulties in the allocation of costs and benefits prevent actors from actively seeking collaboration. There are manifold reasons why the relevant actors might not align to approach an external threat or opportunity. Think of public and private organizations pursuing different objectives (i.e. profits vs. welfare) and thus unable to see the possibility to combining their resources. Or, quite contrary, the relevant actors do not see the opportunity of collaboration because they are direct competitors in the same field or market. Depending on the network at hand the role of an enabling actor can be taken by an individual (e.g. in scientific networks), a firm (e.g. in industrial R&D networks), or a public actor like a government agency or department (e.g. innovation networks addressing basic research and public goods or services).[4] The role of the enabling actor is to contact potential members and inform them about the existing threat or opportunity that is best addressed by collaborating. Therefore, in cases where the need or advantage of collaboration cannot be seen by the relevant actors, an enabling actor is needed to create and design the network in a rather **planned manner**.

Having introduced the two theoretical dimension of our network typology we now turn to the methodology of Social Network Analysis that allows us to distinguish not only the different types of networks according to the mode they are formed and the stage of the life cycle they are in, but also enables us to identify and distinguish the different roles of actors. The next section provides a short introduction to the method and some relevant indicators.

The Method of Social Network Analysis

Social Network Analysis (SNA) is a widely used method to investigate all sorts of social networks. It provides insights in the roles played by different actors as well as in the structure, composition, and dynamic of the network itself. SNA can therefore be used to develop a typology of different network-structures and network-compositions as well as to derive some predictions about how well they are suited to serve a specific purpose.

Because of this multi-dimensionality of social networks the SNA is especially eligible for the investigation of the generation and diffusion of new knowledge within networks. With the words of Müller-Prothmann (2006 p.149) *'social network analysis can serve as a proper*

[4] While the role of the enabling actor is not formally restricted to academic and public institutions, these are likely to be the key ‘champions’ and key actors within such networks (Liebeskind et al., 1996; Argyres and Liebeskind, 1998); this is particularily likely in cases where there is no clear business opportunity for the underlying technology - as is the case for many public goods and services.

method to analyze informal communication of knowledge and, thus, help to localize expertise and transfer of knowledge'.

Following the common dichotomy between 'ego-networks' and 'socio-networks' we divide the relevant SNA measures into 'actor-related measures' and 'network-related measures'.

Actor-Related Measures

From what has been discussed, it became clear that not all actors play the same role in a network. Some actors are very active in their collaborations and entertain many collaborative relationships, whereas other actors are only marginally connected. This is of major importance for the understanding of innovation networks where most often a few actors are responsible for the connection of various knowledge fields and/or the respective actors, whereas others contribute less and exert no influence or power at all. These differences are captured by the actor-related measures of social network analysis as discussed in the following.

One of the most prominent actor related measures is that of *centrality*. The concept of centrality is closely related to that of *power* and *influence*. *'An individual does not have power in the abstract, they have power because they dominate others – ego's power is alter's dependence.'* (Hanneman and Riddle (2005) p. 132). There are, however, several measures of centrality, each of them with a different focal point. While the *degree centrality* accounts for the amount of incoming and outgoing ties an actor has to its direct neighbours, the *closeness centrality* also considers all indirect ties to all other actors in the network and therefore provides us with information about the position of the respective actor within the network. *Betweenness centrality*, in turn, is a measure for the control of information flows within the network. It enables us to identify the importance of an actor by the extent to which it serves as an *intermediary* or *liaison* connecting otherwise unconnected actors or groups of actors. Thus, the Centrality-measures are used to identify the most central and supposingly 'most important' actors of a network. Actors in a central position face fewer constraints and have more opportunities/choices (e.g. in receiving a certain resource) because of a better bargaining position and greater influence. Such central actors can both, foster or hamper the effectiveness of an innovation network in that they connect different knowledge fields or exclude other network members from getting access to certain information.

The most elementary measure of centrality is the ***degree centrality***. Degree, or the degree of connection, thereby means the number of ties an actor has (incoming, outgoing or all). Accordingly, an unconnected actor has a degree of 0. An actor that maintains connections to every other member of the network has a degree of 1. The more similar the degrees of the different actors of a network are, the less central the individual actors are.

The degree-based centrality of an undirected network is calculated by the sum of all ties of an actor n_i with the other actors of the network:

$$C_D(n_i) = d_i = \sum_j x_{ij} = \sum_j x_{ji} \qquad \text{for } i \neq j$$

The variable 'x' stands for the adjacency matrix while x_{ij} are the single elements of this matrix. The 'n' stands for the total number of actors in the network, while n_i denotes one single actor. The inequality of $i \neq j$ simply means, that the relation of an actor to himself is excluded.

To eliminate the influence of network size the degree-based centrality measure has to be normalised. This is done by dividing the C_D by the maximal possible centrality value (i.e. a star network, where one central actor maintains ties to all other actors). *"This is how the Freeman graph centralization measures can be understood: they express the degree of inequality or variance in a network as a percentage of that of a perfect star network of the same size"*.[5] In a network consisting of n actors, the maximal possible centrality value would be n-1, which is the maximal number of ties one actor of the network could have. The normalised degree-based centrality measure is denoted as C'_D and calculated as follows:

$$C_D(n_i) = \frac{\sum_j x_{ij}}{(n-1)} = \frac{\sum_j x_{ji}}{(n-1)} = \frac{C_D}{(n-1)} \qquad \text{for } i \neq j$$

In innovation networks, the centrality measure C_D can be interpreted as the potential *access to external knowledge* sources for a single actor. The higher the centrality measure is, the easier it is for the corresponding actor to access knowledge provided by other actors in his network.

One of the major advantages of the concept of degree centrality is its applicability even to large networks. However, it has one major shortcoming: It only accounts for the ties an actor has to its direct neighbours and therefore neglects the importance of the position within the network. An actor with a low degree centrality (few connections to other actors) could for example be situated in a critical point of the information flow while another actor with a high degree centrality has many redundant ties and is therefore of less importance to the information flow than the first actor. This shortcoming is addressed by the measures of Closeness Centrality and Betweenness Centrality.

The ***Closeness Centrality*** not only includes the direct ties of an actor but all indirect ties to all other actors in the network.[6] Accordingly, closeness centrality does not just measure the proximity of an actor to its direct neighbours, but its proximity to all other actors of the network. Actors that have shorter geodesic distances to other members of the network have a higher closeness. This increases his *efficiency in receiving or distributing information* and, hence, gives them a certain form of *power* – namely from acting as a *'reference point'*.[7] High closeness centrality therefore reflects *the ability to access information through the communication flows within the network.* In innovation networks the closeness centrality describes the strategic position of an actor within the network. If an actor with a high closeness centrality left a network, this would have severe consequences for the functioning of the overall network.

[5] Hanneman und Riddle (2005), p. 137.
[6] While such indirect ties are expected to be weaker and more prone to interference they are easier to maintain in terms of cost and time.
[7] Hanneman und Riddle (2005)

To measure closeness centrality the concept of the geodesics (shortest paths) is used. Analytically, closeness centrality is then calculated as the reciprocal value of the geodesic distances:

$$C_C(n_i) = \frac{1}{\sum_{j=1}^{n} d(n_i, n_j)} = \left(\sum_{j=1}^{n} d(n_i, n_j)\right)^{-1} \qquad \text{for } i \neq j$$

To make different values of closeness centrality comparable it is again necessary to normalise the measure by measuring the mean geodesic distance to all other reachable vertices:

$$C'_c(n_i) = \frac{(n-1)}{\sum_{j=1}^{n} d(n_i, n_j)} \qquad \text{for } i \neq j$$

The ***Betweenness Centrality***, going back to Freeman (1977), is another very common centrality measure. Like the closeness centrality it also considers the indirect ties of actors, but is based on a different concept. While the closeness centrality focuses on the proximity of an actor to all other actors of the network, the betweenness centrality is a measure for the control of *information flows* within the network and the function of single actors as *intermediaries* (the actor *between* other). *Betweenness* therefore is the extent to which a particular actor lies 'between' all the other actors in the network or, in other words, the percentage of times an actor lies on the shortest path 'between' two other actors. Actors that lie on many shortest paths between other vertices have a higher betweenness than others. An actor is the more *powerful* and *influential*, the more indirect ties of other actors are mediated and controlled by him/her. This implicates that actors with a high betweenness centrality do not necessarily have to maintain many direct ties themselves. It is quite possible that a good part of the information flows within a network passes through only a view important ties. Such actors are therefore referred to as *intermediary*, *liaison* or *bridges*. Networks that show a high level of betweenness are more *vulnerable* to a disruption of information flows through strategic behaviour or the retreat of these key-actors.

To calculate the betweenness centrality, it is necessary to first calculate the shortest geodesic paths for all pairs of actors in the network. Looking at all these possible paths, it is tested for every actor in how many of them he plays a mediating role. The more often an actor has a mediating role (i.e. lies on these paths), the higher is his betweenness centrality.

Analytically, the betweenness centrality (C_B) is the probability that the communication between any two actors k and j goes via actor i. Therefore the probability b_{jk} for every pair j and k is calculated by dividing the amount of shortest paths between j and k that go via i $g_{jk}(n_i)$ by the total amount of shortest paths between j and k g_{jk}. These probabilities will then be calculated and summed up for every pair of actors in the network.

$$b_{jk}(n_i) = \frac{g_{jk}(n_i)}{g_{jk}}$$

$$C_B(n_i) = \sum_{j<}^{n} \sum_{k}^{n} b_{jk}(n_i) \qquad \text{for } i \neq j \neq k$$

The betweenness centrality varies between 0 and (N-1)(N-2)/2. To normalise this value, it has to be divided by the maximum possible betweenness-value an actor could achieve. This would be the central actor in a star-network and is (n^2-3n+2)/2 (which is the same than (N-1)(N-2)/2). The normalised betweenness centrality therefore is:

$$C'_B(n_i) = \frac{2C_B(n_i)}{n^2 - 3n + 2}$$

The agent-based measures of SNA, as explained above, enable us to identify the different roles that actors may play in a social network such as innovation networks. Depending on their position and centrality they fulfil a certain function within the network.[8] However, innovations networks also differ with respect to their overall network properties.

Network-Related Measures

While the arguments above belong to the ego-centric perspective in SNA, the following paragraph deals with the 'network perspective'. This top-down proceeding allows for the assessment of the overall characteristics of a network as well as for the identification of its strong and weak parts. From this, implications can be derived concerning the need for changes in the network structure or the absence of an important function (e.g. that of a broker or bridge). Furthermore the number, size and connectivity of sub-structures (such as cliques and clusters) allows for the identification of the opportunities and constrains that single actors and groups of actors face, as well as for the prediction of the evolution of the network.

The ***Network Density*** describes the general level of linkage among the actors in a network. It is the number of actors who are connected to each other, expressed as a percentage of the maximum possible number of connected actors. The network density therefore is the proportion of ties in a network relative to the total number possible (i.e. if all actors of a network are directly connected with each other the density is 100%). It is a valuable measure which describes the overall *coherence* of a network and therefore allows for implications concerning the *speed* of diffusion of information and knowledge within the network and the levels of *social capital* and/or social constraints that actors face (Hannemann und Riddle, 2005). The density is calculated as follows:

$$Density\Delta_k = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} x_{ijk}}{n \cdot (n-1)} \qquad \text{for } i \neq j \neq k$$

While n·(n-1) is the total number of possible ties, k stands for the relation under consideration. The concept is best suited for analysing and comparing data on multiple networks (e.g. networks in different sectors or countries).

[8] Examples for such roles would be **coordinators** (actors who broker connections within the same group), **gatekeepers** (actors who broker connections between their own group and another), **liaisons or boundary spanners** (actors who broker connections between 2 different groups), **peripheral specialists** who are only connected to one other member.

A common approach to assess the embeddedness of the network is to measure the ***mean geodesic distance***. The geodesic distance between two actors is simply the shortest walk connecting them (i.e. the smallest number of edges connecting them). This geodesic path is often also attributed to be the optimal or most efficient connection between two actors. The average geodesic distance for one actor to all others, the variation in these distances, and the number of geodesic paths to other actors may all describe important *similarities and differences between the actors* in *how closely* they are *connected to their entire population*. Other than connectivity it is not about the possibility of reaching another actor, but about the length of this connection. To apply geodesic distance to entire networks we calculate the mean geodesic distances for the network and every actor therein. A small mean geodesic distance indicates that information is likely to reach everyone, and to do so fairly quickly. From the average geodesic distances conclusions can be drawn concerning the *speed of diffusion*, the *cost of exchanges* (the longer the geodesic distance the more expensive the exchange is), the *vulnerability and stability* of the network and the *power and influence as well as constraints and opportunities* of single actors.

Yet another network-measure is the **degree distribution**. It provides some important information about the homogeneity or heterogeneity of the actors. A substantial amount of concentration within a network means that the power of individual actors varies substantially which in turn indicates that positional advantages are rather unequally distributed in this network. As we have seen above, the degree of an actor in a network is the number of connections it has to other actors. Then, the degree distribution is simply the probability distribution of these degrees over the entire network. Thus, the degree distribution measures how concentrated around some central actors the network is. A high degree distribution describes a network in which there are no dominant central actors but many well-connected actors, while a low degree distribution indicates the existence of one or some more central actors. A network characterised by a high degree distribution provides the prerequisites for a *quicker* and *more certain information-flow*. A network characterised by a low degree distribution is dominated by some central actors that control information flows and hold the network together.

A Taxonomy of Innovation Networks

Employing the introduced concepts of the industry life cycle and the network formation we are now able to distinguish six different types of networks according to the stage of their life cycle they are in (formation, growth, and maturity) and the kind of their formation (planned or spontaneous). Networks that are at the same stage of their life cycle are distinguished using the two indicators from Social Network Analysis that showed the most significant difference between our theory-based spontaneous and planned networks.

Table 1: The six types of innovation networks.

	(1) Formation	(2) Growth	(3) Maturity
Spontaneous	S1	S2	S3
Planned	P1	P2	P3

In the following we apply this network typology to identify the distinctive characteristics of the different types of innovation networks based on the discussed indicators and measures from Social Network Analysis. This is done by a comparison of the spontaneous and planned network for the three stages of the innovation network life cycle. To further enhance the understanding we illustrate the different types of networks and provide the respective SNA indicators in brackets. However, these 'stylized networks' are deducted from our theoretical considerations and only serve as an illustrative example to facilitate the understanding and distinction of the different network types.

The Formation Phase - Spontaneous Emergence vs. Planned Creation

At this early stage of network formation the central processes are the composition and structuring of the network. The (formal) structure of a network determines the communication as well as the establishment of shared norms, a common language and mutual understanding. These factors facilitate trust and joint learning.

Since the **spontaneous network** emerges due to some sort of external pressure and the resulting shared interest among a specified group of actors (e.g. from the same industry or region) there is a high likelihood that many of the participating actors already know each other. This might be due to previous market transactions, earlier collaboration or informal relations. The environmental pressure and common interest not only facilitate the achievement of an operational consensus regarding the composition, structure and expected lifespan of the innovation network which leads to more optimistic expectations about the ability and stability of the network, but also facilitates mutual learning (Doz et al., 2000). Thus, if not too many resources are dedicated to finding consensus, spontaneous networks are better suited for exploitative research since its members come from related fields and have rather specialized knowledge and capabilities in a certain field of technology. The resulting network structure is shown in

Other in the **planned network**, here, an enabling actor takes the initiative and forms the network according to his own perceptions. He identifies and invites the other members of the network. By intentionally addressing them and providing the incentives to form a collaborative network, the enabling actor largely determines the composition and structure of the planned network. For this kind of network formation it is not necessary that the members know each other; it is sufficient that the enabling actor knows them. Accordingly, the inner core of a planned network is most likely based on the central actor's personal network or on his pre-existing informal relations (see e.g. Eisenhardt and Schoonhoven, 1996; Pyka, 1997). Depending on the purpose of the network they might come from different fields and sectors and include public as well as private actors. While this heterogeneity of actors implies different aims, cognitive structures and languages which impose an obstacle to efficient knowledge sharing and technology transfer it also increases the potential of cross-fertilization and recombinant innovation (Nelson and Winter 1982; Fleming 2001; Fleming and Sorenson 2001). This makes planned networks better suited for explorative search (March 1991). However, the costs of consensus finding might be relatively high. Other than in the spontaneous network, where consensus is a matter of shared interest, it is the enabling actor who needs to seek this consensus among the members of the network. The resulting network structures are shown in figures 5 and 6.

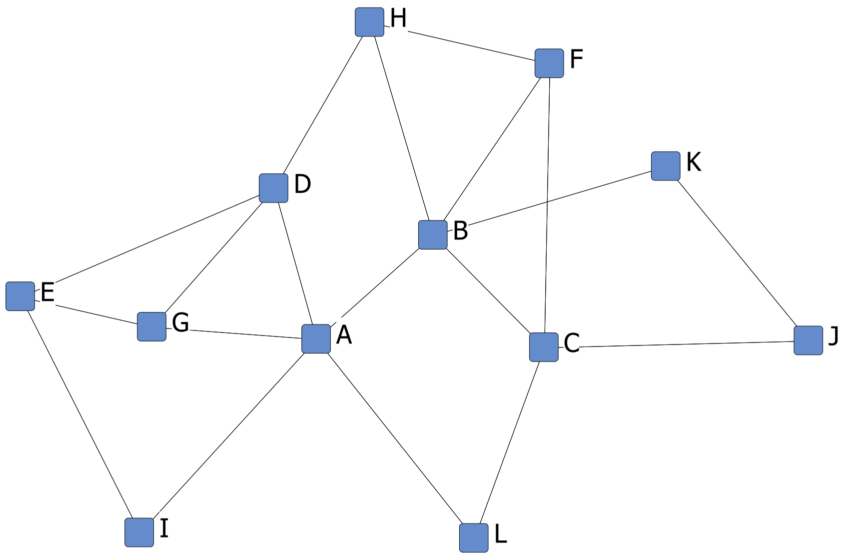

Figure 1: Stylized S1 Network.

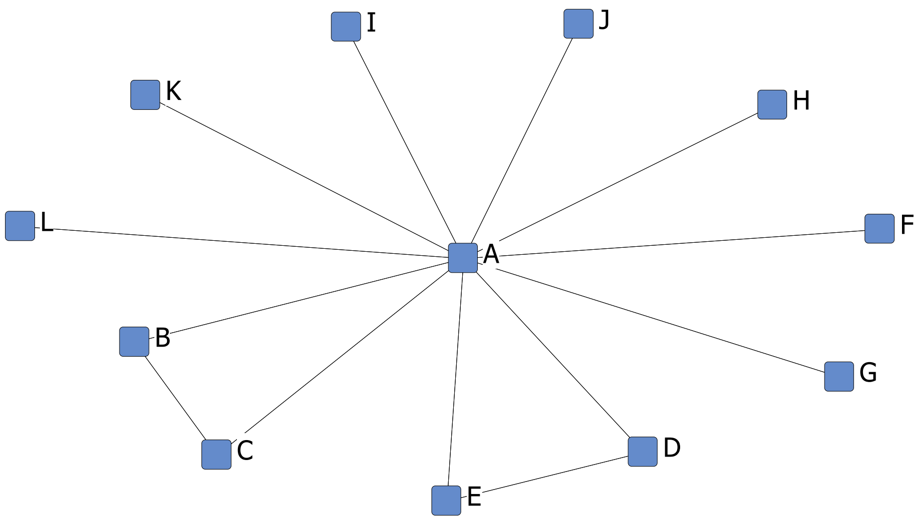

Figure 2: Stylized P1-Network.

Looking at the network indicators it appears that the **degree centrality** and degree distribution (i.e. the number of ties that actors maintain) as a measure of the network centrality is rather high in the planned network as compared to the spontaneous network (96,36% compared to 20%). The enabling actor possesses a normalized degree of 100% (i.e. he is directly connected to all other members of the network), while most actors are peripheral and only connected to him. This leads to a highly unequal degree distribution and a network centralization that leaves all the power, influence and coordination with the enabling actor. In the spontaneous network, in turn, most actors maintain a similar number of relationships, which implies that there is no enabling actor dominating the network, nor are there many peripheral actors that are barely connected. Rather, power and influence are more evenly distributed among the network members.

These differences in actor centrality have also major implications for other network characteristics like, for example, the **network density** (i.e. the number of actors who are connected to each other, expressed as a percentage of the maximum possible number of connected actors). In the spontaneous network the density is relatively high at this initial stage of the network life cycle (0,2879). Therefore, the respective core network is very stable and information and knowledge diffuses quickly throughout the whole network. Furthermore, the network contains a large amount of social capital and its actors are less constrained in the channels through which they exchange knowledge and information. In the planned network, in contrast, the density is relatively low (0,1979), making the stability of the network as well as the knowledge flows highly dependent on the enabling actor.

The Growth Phase - Growth by Attraction vs. Growth by Invitation

As indicated above, the two types of networks also differ in the way they grow. While additional members of a spontaneous network are attracted by the expected benefits of joining the network or are recommended by existing members, the planned network grows the way it was formed: by the initiative of the enabling actor. Thus, in a **spontaneous network** additional members are recruited via a process of attraction and internal recommendation. This leads to a growth process that resembles a snowball-effect: existing members suggest or introduce the new members. The resulting network is strong in itself without having a strong and powerful central actor. In the **planned network** the central actor identifies and invites additional members to the network. This leads to a network in which the central planner is strong, while the network itself is weak (i.e. fragile). The resulting network structure resembles more a hub and spoke network than the snowball pattern of the spontaneous network. The respective network structures are shown in figures 6 and 7.

Because of these different growth processes of spontaneous and planned networks the difference in their centrality persists. Looking at the **closeness centrality** (i.e. the average distance between all actors of the network) we observe that the spontaneous network still shows a relatively low centralization (30,06%) compared to the planned network (98,95%). Thus, because the central actor in a planned network serves as a connector (syn.: boundary spanner or broker) all actors are in relatively close proximity to each other. While this once again confirms the central position of the enabling actor, it also indicates a quicker and potentially more efficient knowledge flow within the planned network.

Accordingly, the **average geodesic distance** between all pairs of actors is relatively shorter in the planned network (1,905). There, no actor is more than two ‘steps’ away from any other actor of the network, because they are connected via the central actor. This is different in the spontaneous network, where some actors have their information to be passed on by several other actors in order to reach their recipient (2,963). This is caused by the snow-ball like growth process during which many members are recommended or attracted by just one actor who himself might not be very well connected.

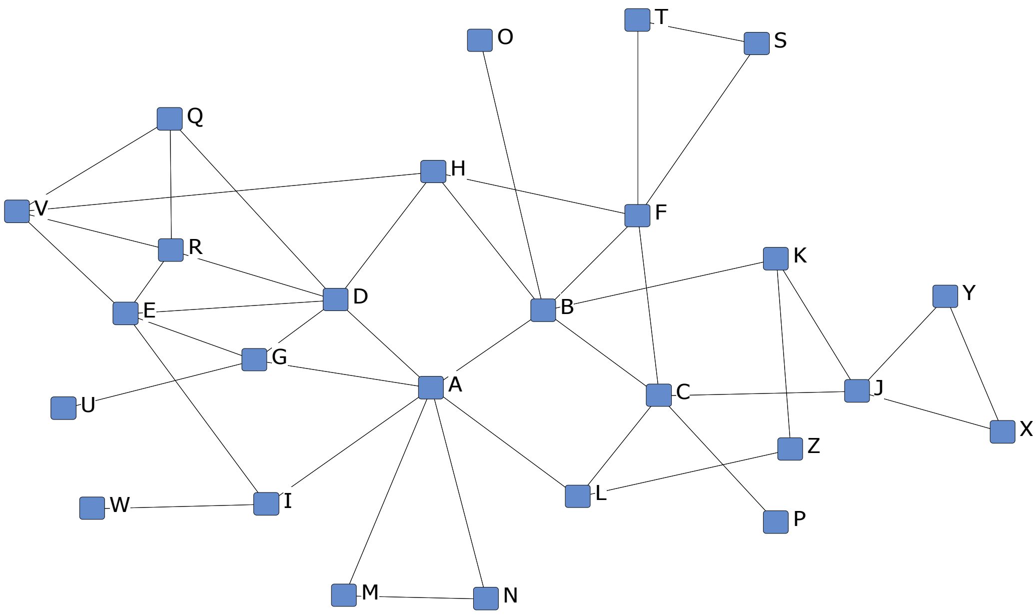

Figure 3: Stylized S2 Network.

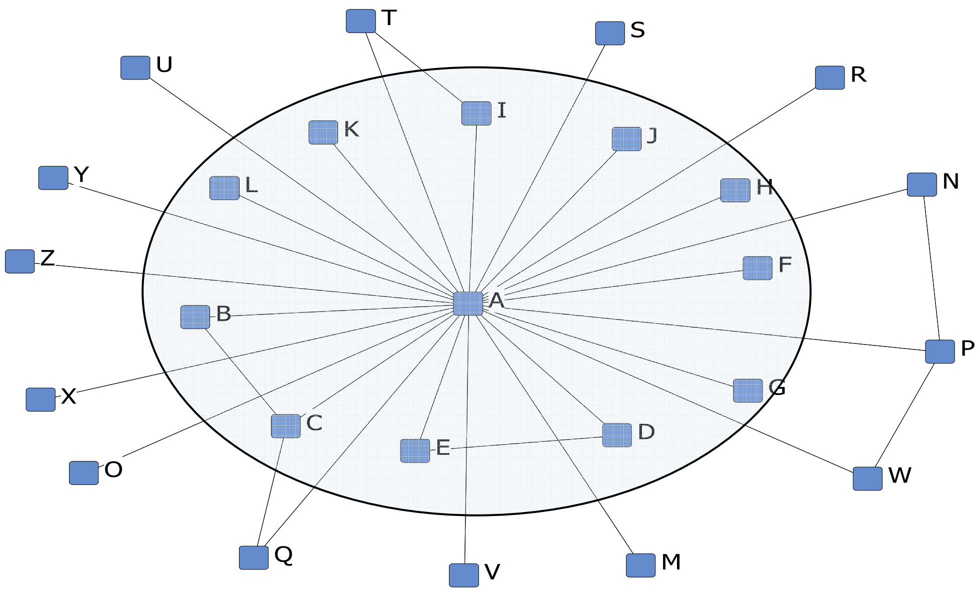

Figure 4: Stylized P2 Network.

The Maturity Phase - Egalitarian Maturity vs. Hierarchical Maturity

The maturity stage of the network life cycle is by no means less dynamic then the first two stages. The repeated and intensifying interaction between the different actors as well as the ongoing fluctuation in the composition of the network also cause significant changes in its structure. Although these dynamics are more prominent in the spontaneous network they are, on a lower scale, also taking place in a planned network. Figures 8 and 9 show the structure of the spontaneous and planned networks at this stage of their life cycle.

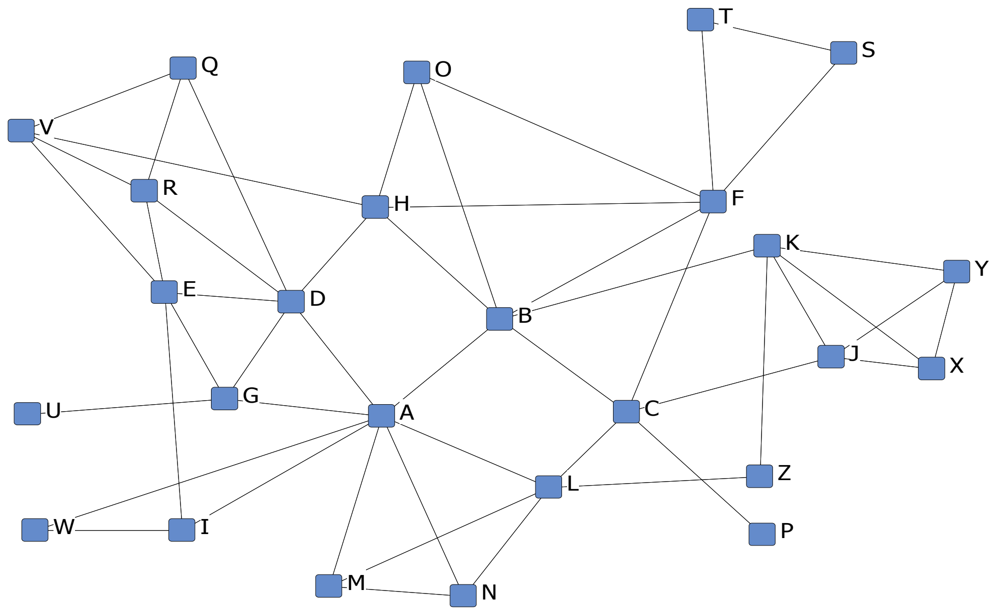

Figure 5: Stylized S3 Network.

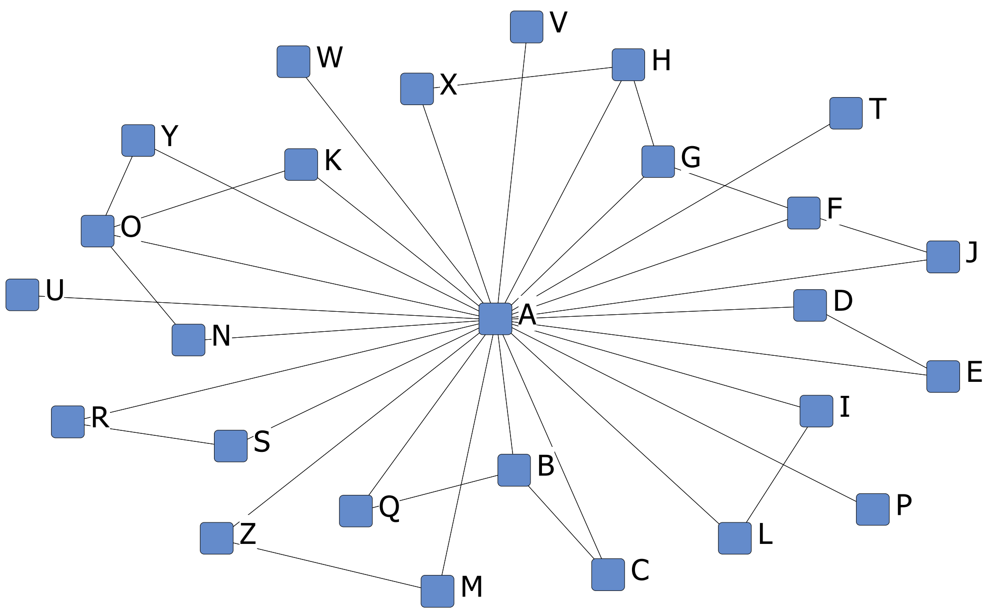

Figure 6: Figure P3 Network.

As in the earlier stages the centrality the ***betweenness centrality*** (i.e. the percentage of times an actor lies on the shortest path 'between' two other actors) is significantly higher in the planned network compared to the spontaneous network (94,45% compared to 29,77%). This is because the enabling actor is connecting all other actors and thus lies on many of the shortest paths between any pair of actors in the network. In the spontaneous network the picture looks different. Here, the majority of the actors lie on the shortest path between a pair of other actors. In the spontaneous network the picture looks different. Thus, the betweenness centrality is more evenly distributed then in the planned network. Because most actors in a spontaneous network are connected to many others, every actor also lies on several shortest paths between two other actors. Therefore we observe the same pattern as in the first two stages, with the planned network showing a very high centralization and the spontaneous network showing a rather low one. Once again this illustrates the outstanding role that the enabling actor plays as a boundary spanner in the planned network. He connects otherwise unconnected actors and controls a large part of the information flow between them. This provides him with enormous power and influence within the network and at the same time makes him ‘the weakest point’ (syn.: cut point) when it comes to network stability. With him retreating the network would dissolve.

These insights are confirmed by the **degree distribution** which is significantly higher in the planned network (95,67 as opposed to 18,33). This indicates that in the planned network most actors are so called ‘peripheral actors’ or ‘peripheral specialists’ (they maintain no direct connections except those to the central actor). In the spontaneous network, in turn, we observe more equally distributed degrees (most actors maintain a similar amount of ties) which is positively related to the speed, quality and certainty of knowledge exchange, as well as the overall stability and density of the whole network.

Table 2 summarizes the predicted differences in the respective SNA characteristics of spontaneous and planned networks in the different phases of their life cycle.

Table 2: Characteristics of the six types of innovation networks.

SNA Indicators		S1	P1	S2	P2	S3	P3
Actor Based Meeasures	**Degree Centrality**	low	high				
	Closeness Centrality			low	high		
	Betweenness Centrality					low	high
Network Based Measures	**Density**	high	low				
	Mean Geodesic Distance			high	low		
	Degree Distribution					low	high

This taxonomy is based on a highly stylized concept of network evolution. Two scenarios that are likely to be observed in real world innovation networks are the growth by preferential attachment of spontaneous networks and the retreat of the central actor at a certain point in the life cycle of planned networks. Both, the process of preferential attachment as well as the critical event of the central actor retrieving from the network have a major impact on the network structure and performance. We will discuss these concepts and their implications in the following section.

Alternative Dynamics – Growth by Preferential Attachment and the Delegating Retreat of the Enabling Actor

Empirical evidence suggests that networks often grow by **preferential attachment** (Albert and Barabasi, 2002).[9] Other than in the growth by recommendation as underlying our typology, this process is based on the idea that potential new actors try to connect to the most central (powerful, influential) actors. Following the logic of this algorithm, new actors prefer to attach themselves to existing actors according to the latter's degree. The benefit of linking to an actor with a high degree is that this provides the new actor with short pathways and a high connectivity within the network. Preferential attachment is a likely scenario for **spontaneous innovation networks.** Linking themselves to a central actor provides the new actors with better access to the knowledge that flows within the network. Yet another argument for preferential attachment is reputation. As degree centrality is also a measure of prestige and influence, the new actors benefit from being linked to a central actor because this enhances their own prestige and reputation which, in turn, increases their prospects of collaborating with other attractive partners.

The growth by preferential attachment has severe consequences for the resulting network structure. If the probability of a new actor to connect with an already existing actor depends on the latter's degree, the networks produced by this algorithm show a skewed, scale-free degree distribution. Those actors who were relatively central (i.e. had above average degrees) in the first stage of the network life cycle grow even more central during the following stages. Thus, the process of preferential attachment underlines and even enhances the power and influence of central actors within a network. The resulting network structure resembles more a hub and spoke network than the snowball pattern we described above. Thus, the growth by preferential attachment of the spontaneous network resembles the growth pattern of a planned network, where every actor attaches himself to the enabling actor (the actor with the highest degree centrality), except that there is not just one central actors but several.

A very likely scenario in the evolution of **planned innovation networks** is the retreat of the enabling actor (central actor) at a certain point in network evolution. This would redistribute the network positions of many actors and provide the opportunity to significantly change the overall network structure. Two theoretical considerations reinforce the likelihood of this event. First, every actor, including the enabling actor, has only limited resources and capacity at his disposal (e.g. time, financial resources, information processing capacity etc.). Therefore he cannot play the central role indefinitely but needs to delegate at least part of his responsibilities to other members or retreat from the network once his resources are exhausted. A sec-

[9] Powell et al. (2005) find evidence for scale-free degree distributions in the collaborations between biotechnology firms. This tendency of firms to connect to highly connected firms is also tested empirically by Powell et al. (2006) but has lead to ambiguous results. In reality most networks exhibit power law distributions with exponents smaller than three in their degrees. One explanation why the actual observed distribution is less skewed than one would predict from preferential attachment is that 'proximity matters'. Following this reasoning new actors – even though attracted by the ones with highest connectivity – often connect to actors with lower degree if these are more proximate in any of the five distinguished dimensions of proximity (i.e. cognitive, organizational, social, institutional, and geographical proximity).

ond rational is that the enabling actors' only intention might be to initiate the network formation and ensure its efficiency by composing and structuring it according to his perception before retreating from his central position. This second scenario describes what is usually assumed concerning the intention of a public actor promoting basic research in a certain field or fostering innovative collaboration on a regional level. This is confirmed Doz et al. (2000) who find that public actors are often only interested in providing the necessary environment before moving on to other projects.

Looking at the indicators from Social Network Analysis that we used to distinguish planned and spontaneous networks it becomes clear that the retreat of the central actor would have severe consequences for the structure and functioning of the network. The high values of centrality observed in the planned network at all stage of its life cycle illustrate the outstanding role that the enabling actor plays as an information broker, intermediary or boundary spanner. He connects otherwise unconnected actors and controls a large part of the information flow between them. As we have established before, he is extremely well informed about what is going on in the network which gives him enormous power and influence within the network but at the same time makes him 'the weakest point' ('cut point') when it comes to network stability. With him retreating in an unplanned manner, the network would simply dissolve. Thus, his retreat needs to be carefully prepared. There are at least three possible scenarios or 'exiting strategies' for the central actor: a) he could install one successor who takes over his position and responsibilities; b) he could install a number of central actors who, together, fulfil his role; or c) he could establish the necessary amount of direct ties between all actors of the network, so the network is stable and functional without any central actor. Considering these alternatives it becomes clear that option a) would not solve the problem of limited resources and capacity and, thus, is rather unlikely. Also it would have no significant influence on the network structure. Option c) in turn would lead to a network structure that is similar to the one we assumed for the spontaneous network at the maturity stage. However, intentionally establishing the necessary connectivity amongst the heterogeneous actors of a planned network seems an unrealistic endeavour. Thus, the most promising and also most likely alternative is option b). By delegating the responsibility for different tasks or technological fields to different actors, the retreating central actor ensures that their capacity is not exceeded and, at the same time, renders the possibility for labour division and specialization. All actors serving a certain function, working on the same problem or belonging to a certain technological field will be linked to one rather central actor. This allows for a closer and more intense interaction within these groups of rather homogeneous actors and thereby leads to the establishment of further direct links between these actors. The resulting network structure is characterized by a group of central actors (i.e. the central core) that are densely connected among themselves and to the members of their respective specialized groups. This basically resembles the network structure of spontaneous networks growing by preferential attachment. Thus, the two alternative developments we described here both lead to a network structure that combines the advantages of short average path length with a high degree of clustering (see figures 10 and 11). This network structure is referred to as a **'small world'** and is considered to be especially advantageous for the creation and diffusion of new knowledge – i.e. for innovation networks.

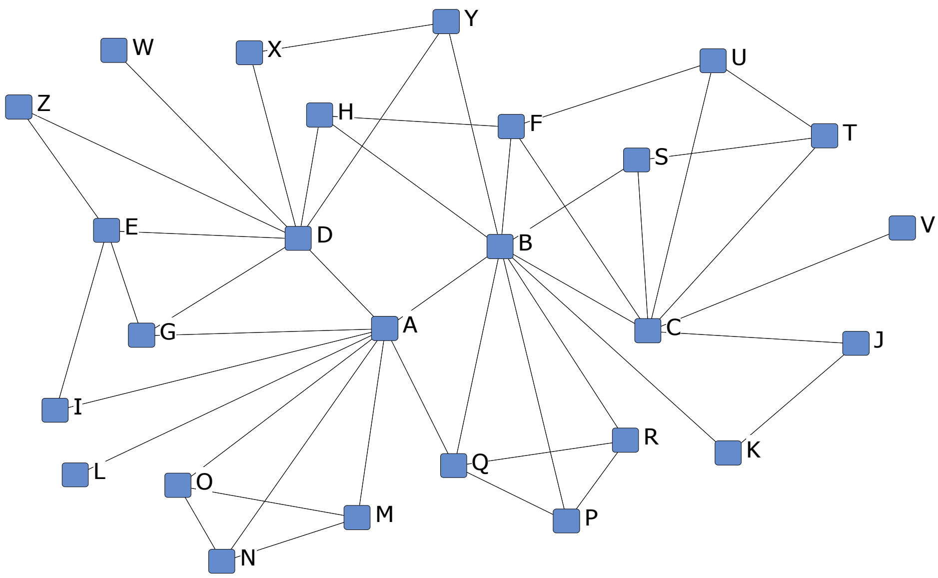

Figure 7: Stylized S3 Network resulting from Growth by Preferential Attachment in S2.

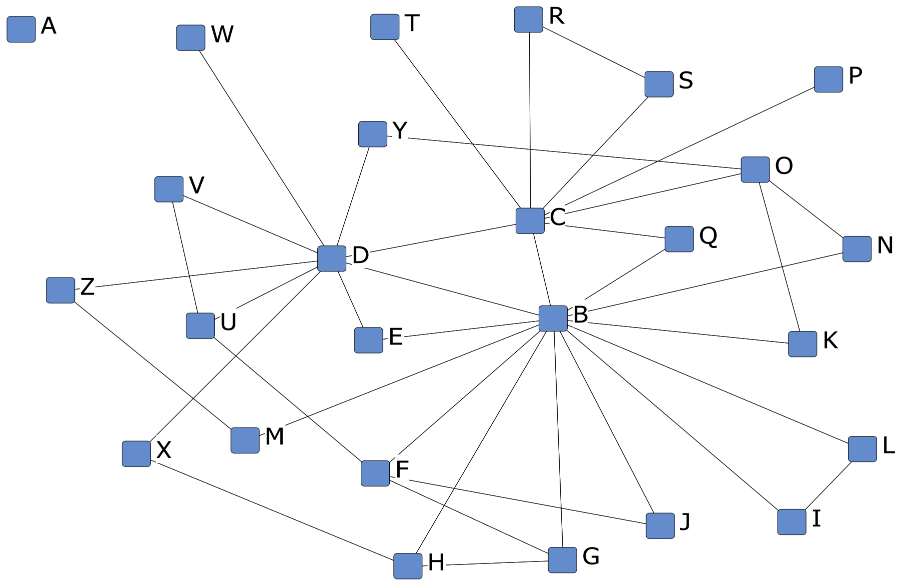

Figure 8: Stylized P3 Network after the Retreat of the Central Actor.

Following the arguments presented in this paragraph we expect that over time the distinction of the two types of networks becomes somewhat blurred. As networks evolve they change with respect to many, if not most, of their characteristics (see e.g. Madhavan et al., 1998). The network composition might change with the entrance of new actors and the exiting of others. New relations might be established while others get dissolved. The content and extent of established relations might also change as well as the initial purpose or objective of the network. Thus the boundary between the two types of networks becomes permeable. What started as a planned network of largely unrelated actors might become more and more like a spontaneous network as new relations are formed, trust is built and the formal structures are underpinned by informal relations (Pyka, 1997; Lorenzoni and Lipparini, 1999). After interacting repeatedly on a formal basis, informal ties are created that even outlast the formal collaboration. Following Hakanson (1989), we therefore postulate that with an increasing duration of formal cooperation, formal network structures mutate to informal relationships as mutual trust and confidence between the partners is built. Spontaneous networks in turn might be threatened by some sort of lock-in: Constrained by a strong common interest and similar capabilities and knowledge bases spontaneous networks become inflexible and unable to recognize alternative approaches in responding to changes in their environment (Uzzi, 1997). Thus, they might have to change their focus from exploiting their existing knowledge base to the exploration of new alternatives. As argued above, this is better achieved in a network that shows the characteristics of a planned network (i.e. strong central actor, formalization, heterogeneous actors etc.). Thus, if the network is a success or shows potential for further collaboration a central actor might take the initiative and create a new network on basis of the existing relations. From this we conclude that long-term network survival depends on the ability to combine the advantages of the two types of networks. We have argued that while the mode of network formation might have an enduring impact it does not necessarily determine the network structure at later stages of the network life cycles. Depending on the growth-process of spontaneous networks and the network-shaping activities of the enabling (central) actor in the planned network, we can also expect some convergence towards the favourable small world network structure. This indicates a process of convergence between the two network types. The convergence of the two forms of networks can be so complete, that it is no longer possible to distinguish the two types of networks using the indicators from SNA.

Concluding Remarks

Drawing from theory and existing empirical evidence we proposed that knowledge-based networks emerge either spontaneously due to environmental pressure and a resulting shared interest or by a ‘planned’ process involving an enabling actor initiating its formation and controlling its growth. Which way a network forms itself depends on the prevalent conditions. The initiation stage with the process of network formation is probably the most important stage in the life cycle of an innovation network since it sets the stage for its further evolution. Employing indicators from Social Network Analysis we are able to distinguish these persistent differences between spontaneous and planned innovation networks along their life cycle.

However, theory and empirical evidence also indicate that the mode of network formation does not determine all future developments and outcomes of the respective networks. We find plausible arguments for alternative development paths that lead to a rather similar network structure. In the case of the spontaneous network we suggest the concept of preferential attachment as an alternative growth pattern which has major implications concerning the resulting network structure at the maturity stage. A spontaneous network growing by preferential attachment leads to a network that is characterized by a short average path length and a relatively high clustering coefficient. These characteristics describe what has been labelled a ‘small world network’ and are associated to quick knowledge diffusion and the possibility to exchange even complex knowledge. Because of these characteristics, the small world network is widely acknowledged as a highly efficient network structure, especially in the context of knowledge exchange and innovation.

We observe a very similar network structure for planned networks in which the enabling actor retreats from its central position by delegating his functions to a group of actors. This bears some important implications for the changing role of actors as well as for the management of public private innovation networks in services (ServPPINs). Focusing on public private innovation networks we argue that the retreat of the central actor (e.g. a public body) at the mature stage of a planned ServPPIN is not only a very likely and empirically confirmed scenario but also constitutes a critical event that has severe consequences for the functioning and stability of the network. Since the central actor of a planned ServPPIN serves as the connector (also boundary spanner or information broker) he is essential for the knowledge flow as well as the overall stability of the network. Thus, if he retreats without ensuring the viability and stability of the network, the ServPPIN would dissolves. Due to the limited capacities and resources that the individual actors have at their disposal and because of the possibility to render efficiency-gains through labour division and specialization associated we suggest what we call a 'delegating retreat'. This scenario envisages the division and delegation of the retreating (public) actor's functions and power on the shoulders of several public and private actors. These actors should be members of the network for quite some time, maintain direct ties to their relevant peers within the network, and must have proven to be capable of handling this responsibility. However, the resulting flattening of the hierarchy not only imposes more responsibility on the newly assigned central actors but on all members of the network. Even the formerly peripheral actors are now obliged to establish new relationships and to interact more intensely not only with the new central actors but also with the other members of their respective sub-group. While this constitutes a major challenge for the individual communication capabilities of the actors, it allows for a more intensive exploitation and exploration of new solutions at the cluster and network level respectively.

Another important aspect in this development is timing. The disruptions and implications associated with the retreat of the central enabling actor also depend on the current stage of the network's life cycle. To minimize the negative effects and to smoothen the process of restructuring the retreat should take place at a stage at which the network itself is stable i.e. a mature stage. At this stage, the network is characterized by a high network density and connectivity which ensure its capability to absorb the shocks resulting from the retreat of its central actor.

References

Abernathy, W., Utterback, J. (1978) Patterns of industrial innovation, in Technology Review 80(7): 40-47.

Anderson, Michael, L. Tushman; Administrative Science Quarterly, Vol. 35, 1990

Argyres, N. and Liebeskind, J. (1998), Privatizing the intellectual commons: Universities and the commercialization of biotechnology, Journal of Economic Behavior and Organization, 35, 427-454.

Ayres, R., Ayres, L. & Rade, I. (2003), The Life cycle of Copper, Its Co-products and Byproducts, Kluwer Academic Publishers, Massachusetts.

Barabasi, A.L., Albert, R. (1999) Emergence of scaling in random networks. Science, 286(5439): 509-512.

Barnes, J. (1974) Social Networks, Module in Anthropology, No. 26, Addison-Wesley, Reading/MA.

Barras, R. (1986), Towards a Theory of Innovation in Services, Research Policy, Vol. 15, 161-173.

Barras, R. (1990), Interactive Innovation in Financial and Business Services: The Vanguard of the Service Revolution, Research Policy, Vol. 19, 215-237.

Boschma, R.A. (2005) Proximity and innovation. A critical assessment. Regional Studies, 39(1): 61–74.

Breschi, S., Lissoni, F. (2003) Mobility and social networks: Localised knowledge spillovers revisited. CESPRI Working Paper 142. http://www.cespri.unibocconi.it/, forthcoming in the Annales d'Economie et de Statistique.

Breschi, S., Lissoni, F. (2006), Mobility of inventors and the geography of knowledge spillovers, New evidence on US data. CESPRI Working Paper 184. http://www.cespri.unibocconi.it/

Burgelman, R. E. (1983), A model of the interaction of strategic behavior, corporate context and the con- cept of strategy', Academy of Management Review, 8, pp. 61-70.

Burt R. 1992. Structural Holes. Chicago: University of Chicago Press

Buzzell, Robert (1966), Competitive Behavior and Product Life cycles, in New Ideas for Successful Marketing, John Wright and Jac Goldstucker, eds., American Marketing Association, Chicago.

Cantner, U., Pyka, A. (1998), Absorbing Technological Spillovers, Simulations in an Evolutionary Framework, *Industrial and Corporate Change*, Vol. 7.

Caracostas, P. and Muldur, U. (2001), The emergence of a new European Union research and innovation policy, In Laredo, P. and Mustar, P. (eds.), Research and innovation policies in the new global economy, Edward Elgar: Cheltenham, UK.

Cohen, Wesley, M. & Levinthal, Daniel A. (1990) Absorptive Capacity: A New Perspective on Learning and Innovation, ASQ, 35, 128-152.

Coombs, R. and Metclafe, J.S. (2002), Innovation in pharmaceuticals: Perspectives on the coordination, combination and creation of capabilities, Technology Analysis and Strategic Management, 14, 261-271.

Cox, Jr., William (1963), Product Life cycles and Promotional Strategy in the Ethical Drug Industry, Ph.D. dissertation, University of Michigan.

Cunningham, M. T. (1969), The Application of Product Life cycles to Corporate Strategy: Some Research Findings, Brit. J. Market. : 32-44.

Dosi, G. Technological paradigms and technological trajectories. Research Policy (1982) 11:147–162

Doz, Y. L., Olk, P. M. and Smith Ring, P. (2000), Formation processes of R&D consortia: which path to take? Where does it lead? Strategic Management Journal; Volume 21, Issue 3, pages 239–266.

Ebersberger, B., Jonard, N. and Pyka, A. (2005), Small world and scale-free networks in bio-tech collaboration, mimeo.

Edquist, C., Johnson, B., 1997. Institutions and organizations in systems of innovation. In: Edquist, C. (Ed.), Systems of Innovation: Technologies, Institutions and Organizations. Pinter, London.

Eisenhardt, K.M. and Schoonhoven, C.B. (1996) 'Resourcebased view of strategic alliance formation: strategic and social effects in entrepreneurial firms', Organization Science 7(2), pp. 136-150.

Etzkowitz, H., Leydesdorff, L., 2000. The dynamics of innovation: From National Systems and ‘‘Mode 2” to a Triple Helix of university–industry–government relations. Research Policy 29, 109–123.

Fleming, L. (2001). "Recombinant Uncertainty in Technological Search." Management Science 47(1): 117-132.

Fleming, L. and O. Sorenson (2001). "Technology as a complex adaptive system: evidence from patent data." Research Policy 30(7): 1019-1039.

Freeman, C. (1991) Networks of innovators: A synthesis of research issues, Research Policy 20, pp. 499-514

Freeman, Linton C. (1977): A set of measures of centrality based on betweenness. Sociometry 40; p. 35-41.

Galloui, C., Galloui, J. (2000), Neo-Schumpeterian Perspective on Innovation in Services, in : Boden, M., Miles, I. (Eds.), Services and The Knowledge-Based Economy, Continuum, London.

Gertler, M.S. (1995) 'Being there': Proximity, organization, and culture in the development and adoption of advanced manufacturing technologies. Economic Geography 71: 1–26.

Gort, M., Klepper, S., 1982, Time paths in the diffusion of product innovations, *Economic Journal*, 92, 630-653.

Granovetter, M. (1973) The strength of weak ties, American Journal of Sociology 78, pp. 1360-1380.

Granovetter, M. (1985) Economic action and social structure: the problem of embeddedness. American Journal of Sociology, 91: 481-510.

Guimerà, R., Amaral, L. (2004): Modeling the world-wide airport network, European Physical Journal B 38, 381-385.

Hagedoorn, J. (2002). Inter-firm R&D partnerships: an overview of major trends and patterns since 1960, Research Policy, 31(4), pp. 477-492

Hakanson, H. (1989), Corporate Technological Behaviour: Cooperation and Networks, Routledge, London.

Hanneman, Robert A. / Riddle, Mark (2005): Introduction to social network methods. Riverside: University of California. URL: http://www.faculty.ucr.edu/~hanneman/nettext/ [Stand: 22. Oktober 2006].

Hardeman, S., Frenken, K., Ponds, R. (2008) Science, Nature and the changing nature of science, manuscript, Utrecht University, in progress.

Hargadon, A. B. (2002). "Brokering knowledge: Linking learning and innovation." Research in organizational behavior 24: 41-86.

Jackson, M. O. and A. Wolinsky (1996) A Strategic Model of Social and Economic Networks, Journal of Economic Theory 71, pp. 44-74.

Jovanovic, B., and MacDonald, G., 1994, The life cycle of a competitive industry, *Journal of Political Economy*, 102, 322-347.

Jovanovic, B., and Tse, C., 2006, Creative destruction in industries, mimeo.

Klepper, Steven, 1996. "Entry, Exit, Growth, and Innovation over the Product Life cycle," American Economic Review, American Economic Association, vol. 86(3), pages 562-83

Klepper, Steven, 1997. "Industry Life cycles," Industrial and Corporate Change, Oxford University Press, vol. 6(1), pages 145-81

Klepper, Steven; Simons, Kenneth L., 2005, "Industry Shakeouts and Technological Change", *International Journal of Industrial Organization*, 23(1-2), 23-43.

Koza, M. and A. Y. Lewin (1998). The co-evolution of strategic alliances, Organization Science, 9, pp. 255-264.

Liebeskind, J.P., Oliver, A.L., Zucker, L. and Brewer, M. (1996), Social networks, learning, and flexibility: Sourcing scientific knowledge in new biotechnology firms, Organization Science, 7, 428-443.

Lorenzoni, Gianni and Lipparini, Andrea (1999), The Leveraging of Interfirm Relationships as a Distinctive Organizational Capability: A Longitudinal Study. Strategic Management Journal, Vol. 20, No. 4, pp. 317-338.

Madhaven, R., B. R. Koka and J.E. Prescott (1998). 'Networks in transition: How industry events reshape interfirm relationships', Strategic Management Journal, 19(5), pp. 439-460.

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. Organization Science 2(1): 71.

McMillan, G.S., Narin, F. and Deeds, D.L., (2000), An analysis of the critical role of public science in innovation: The case of biotechnology, Research Policy, 29, 1-8.

Moreno, J. L. Who Shall Survive? A New Approach to the Problem of Human Interrelations. Washington, D.C.: Nervous and Mental Disease Publishing Company, 1934.

Müller-Pothmann, T. (2006), Leveraging Knowledge Communication for Innovation – Framework, Methods and Applications of Social Network Analysis in Research and Development.

Nelson, R. and S. Winter (1982). An Evolutionary Theory of Economic Change. Cambridge, Harvard University press.

Nelson, R., and Winter, S., 1977, In search of useful theory of innovation, *Research Policy*, 6, 36-76.

Nooteboom, B. (1999), Inter-Firm Alliances, Analysis and Design, Routledge, London.

Orsenigo, L. (1989), The emergence of biotechnology: Institutions and markets in industrial innovation, London: Pinter.

Ozman, M. (2006) Knowledge Integration and Network Formation, Technological Forecasting and Social Change, 73, 9, 1121

Ponds, R., van Oort, F.G., Frenken, K. (2007) The geographical and institutional proximity of research collaboration. Papers in Regional Science, 86: 423–443.

Powell WW, Koput K, Smith-Doerr L (1996) Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. Administrative Science Quarterly 41: 116-145

Powell, W. W. (1990). 'Neither market nor hierarchy: Network forms of organization'. In L. L. Cummings and B. M. Staw (eds.), Research In Organizational Behavior, Vol. 12. JAI Press, Greenwich, CT, pp. 295-336.

Powell, W.W., White, D.R., Koput, K.W., Owen-Smith, J. (2005) Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences. American Journal of Sociology 110(4):1132-1205.

Pyka and Saviotti, 2005: The Evolution of R&D Networking in the Biotech Industries, Journal of Entrepreneurship and Innovation Management 5(1/2) pp 49-68)

Pyka, 1997: Informal Networking, Technovation 17(4) pp 207-220.

Pyka, 2007: Innovation Networks. In: Elgar Companion To Neo-Schumpeterian Economics, Edward Elgar Publishing, Cheltenham, pp 360-385.

Pyka, A., Windrum, P., 2003: The Self-Organisation of Strategic Alliances, Economics of Innovation and New Technology, Vol. 12, 245-268

Radcliff-Brown, A. R. (1965 (1952)), Structure and Function in Primitive Society - Essays and Adresses, Cohen & West, London.

Rallet, A., Torre, A. (1999) Is geographical proximity necessary in the innovation networks in the era of global economy? Geojournal 49(4): 373-380.

Sahal, D., 1985, Technology guide posts and innovation avenues, *Research Policy*, 15, 285-305.

Saviotti, P. P., Pyka, A., Krafft, J. (2007) On the Determinants and Dynamics of the Industry Life cycle. Mimeo.

Saxenian, A. (1994), Regional Advantage: Culture and Competition in Silicon Valley and Route 128, Harvard University Press: Cambridge, MA.

Scott, John (1994): Social network analysis. A handbook, London u.a: Sage.

Tushman, M., P. Anderson. 1986. Technological discontinuities and organizational environments. Admin. Sci. Quart. 31 439-465.

Tychy, N.M., Fombrun, C. (1979b) Network Analysis in Organizational Settings, Human Relations 32, pp 923-965.

Tychy, N.M., Tushman, L., Fombrun, C. (1979a) Social Network Analysis Organizations, Academy of Management Review, 4, pp. 507-519

Utterback, J. (1994). Mastering the Dynamics of Innovation. Boston, Harvard Business School Press.

Utterback, J. and W. Abernathy (1975). A Dynamic Model of Process and Product Innovation. Omega 3(6): 639-656.

Utterback, J., and Suarez, F., 1993, Innovation, competition and industry structure, *Research Policy*, 22, 1-21.

Uzzi, B. (1996) The sources and consequences of embeddedness for the economic performance of organizations: The network effect. Amer. Soc. Rev. 61 674-698.

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embed- dedness, Administrative Science Quarterly, 42, pp. 35-67.

Van Beuzekom, B. (2001), Biotechnology statistics in OECD member countries: Compendium of existing national statistics, OECD: Paris.

Van Reenen, J. (2002), Economic issues for the UK biotechnology sector, New Genetics and Society, 21, 109-130.

Vernon, R., 1966, International investment and international trade in the product cycle, *Quarterly Journal of Economics*, 87, 2.

Walsh, V. and Rodorfos, G. (2002), Technological and organizational innovation in chemicals and related products, Technology Analysis and Strategic Management, 14, 273-298.

Williamson, O. (1985), The Economic Institutions of Capitalism, New York, The Free Press.

Windrum, P. (2007) Innovation in Services, in Hanusch, H., Pyka, A., Elgar Companion to Neo-Schumpeterian Economics, Elgar, Cheltenham, UK.

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